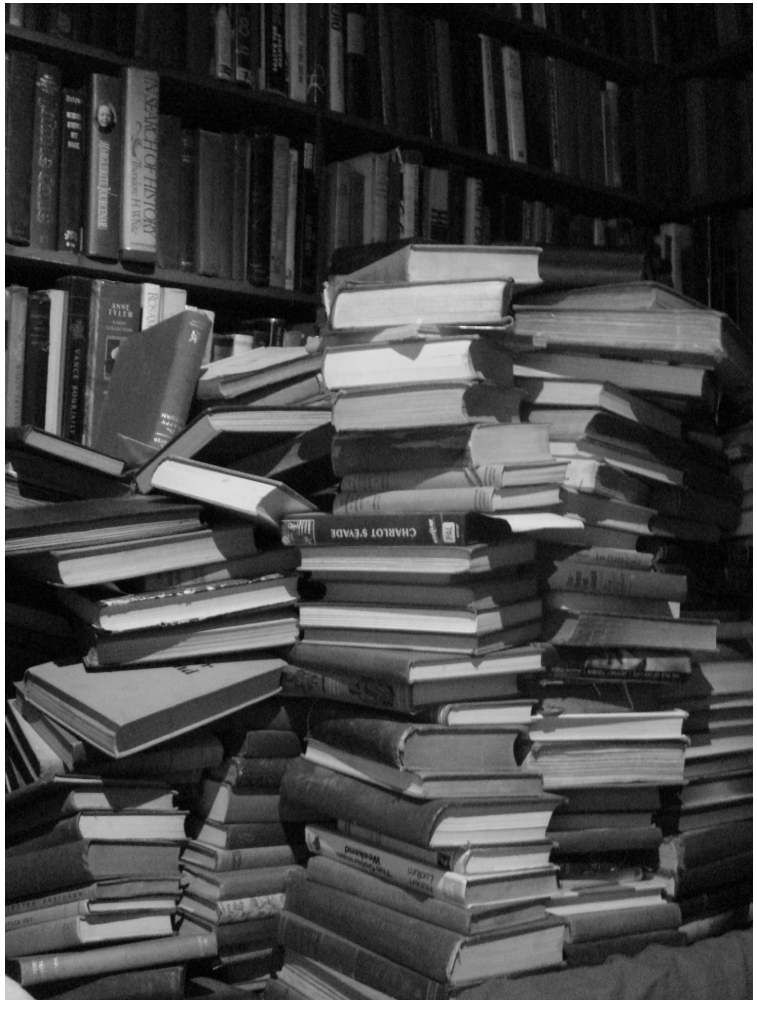
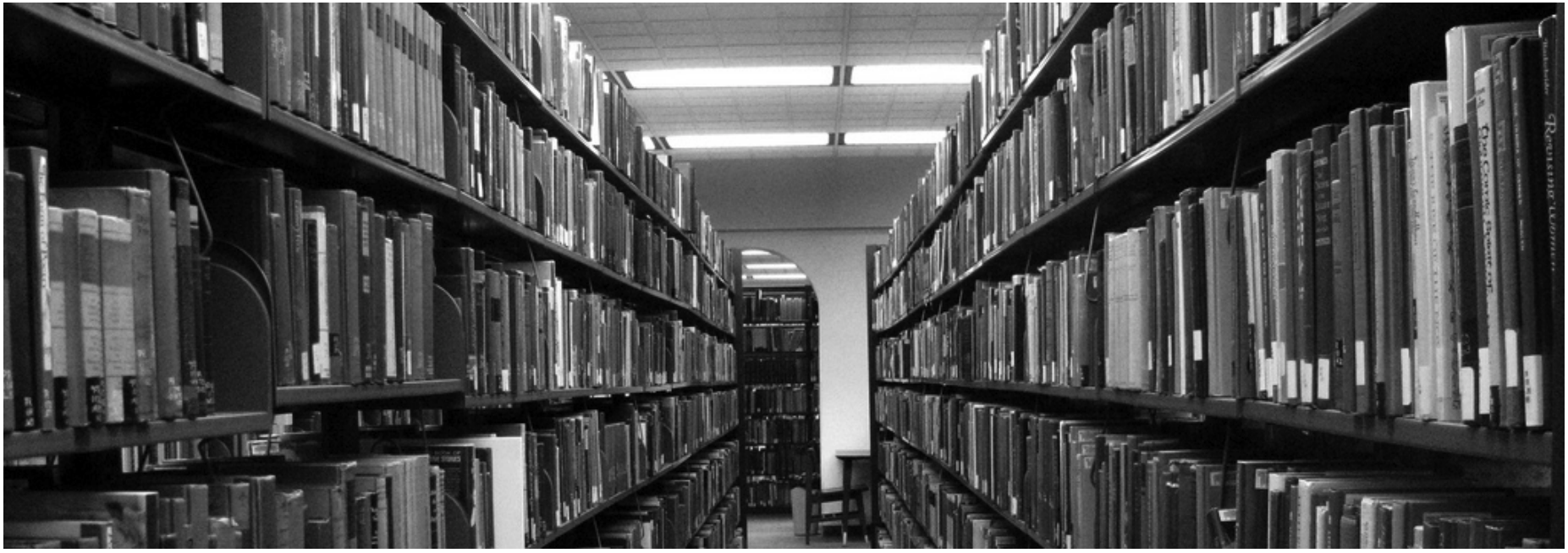
Probabilistic Topic Models and User Behavior

David M. Blei
Columbia University

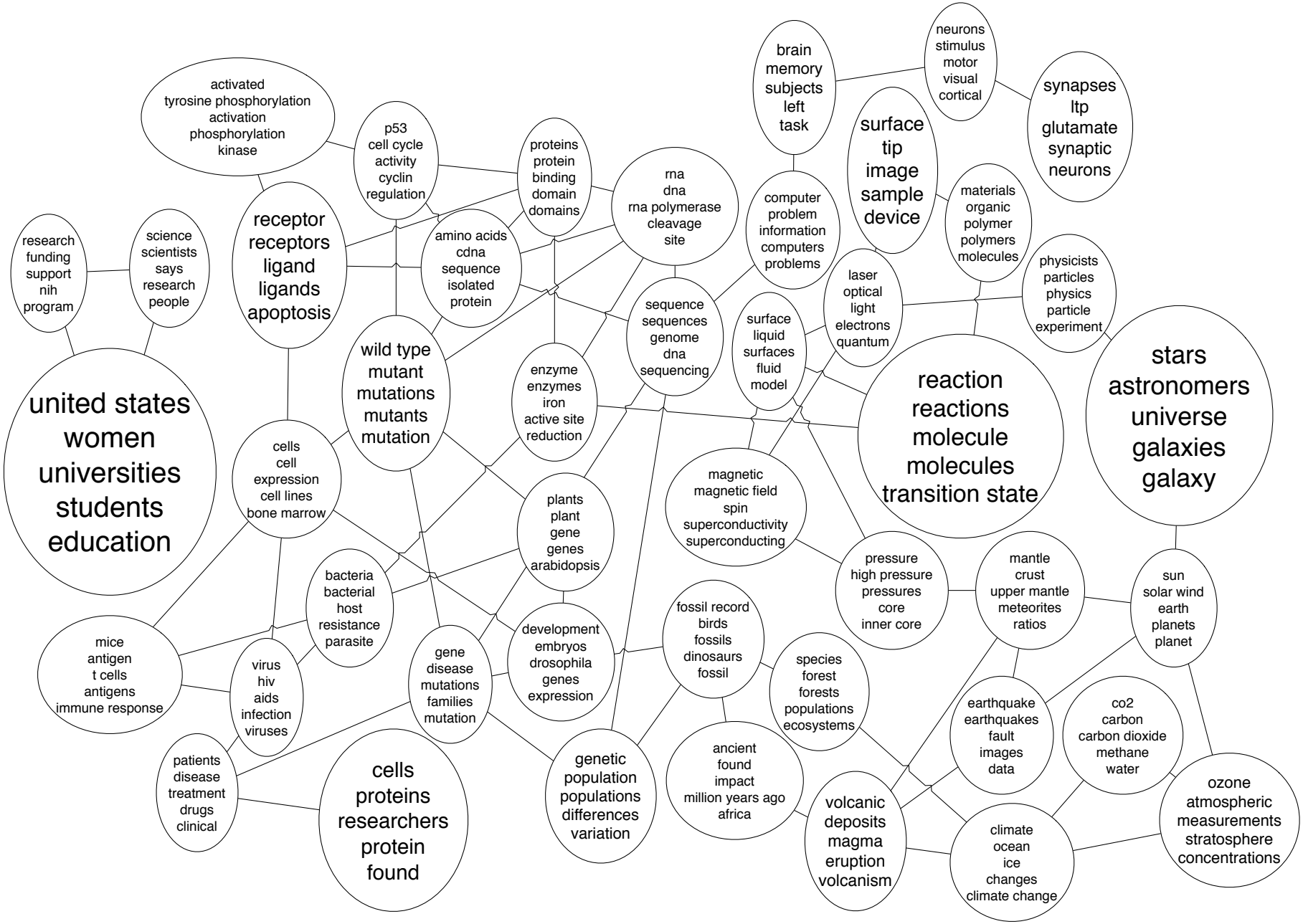


- **ORGANIZE**
- **VISUALIZE**
- **SUMMARIZE**
- **SEARCH**
- **PREDICT**
- **UNDERSTAND**

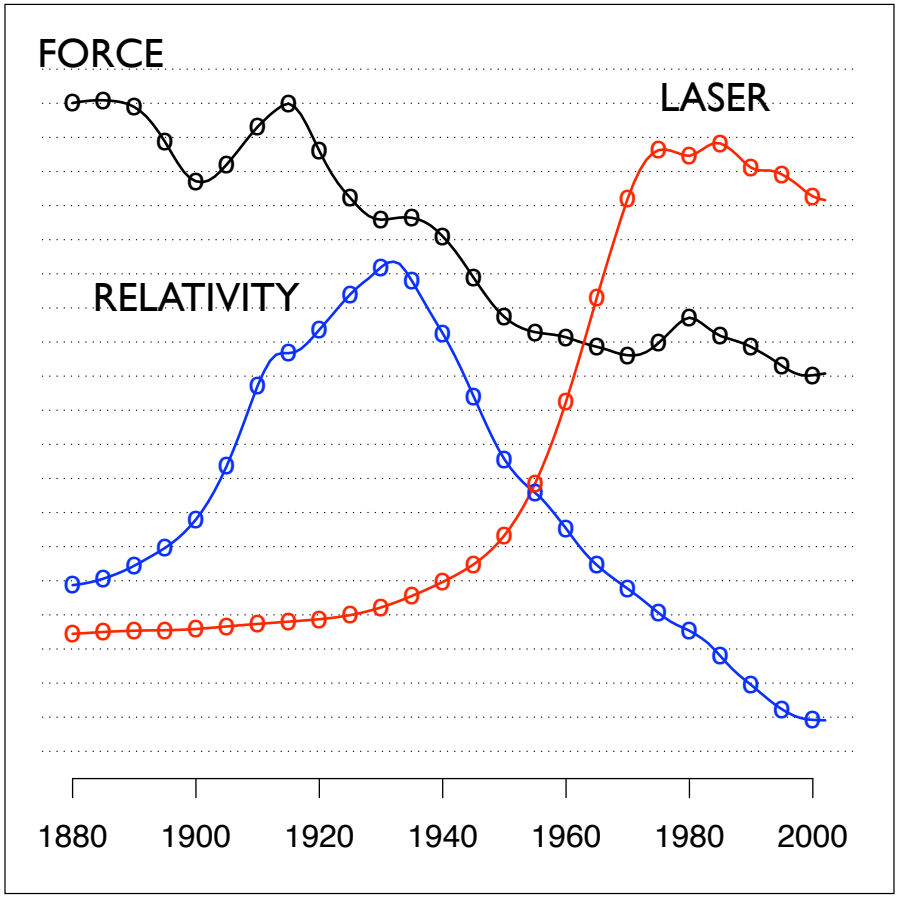


TOPIC MODELING

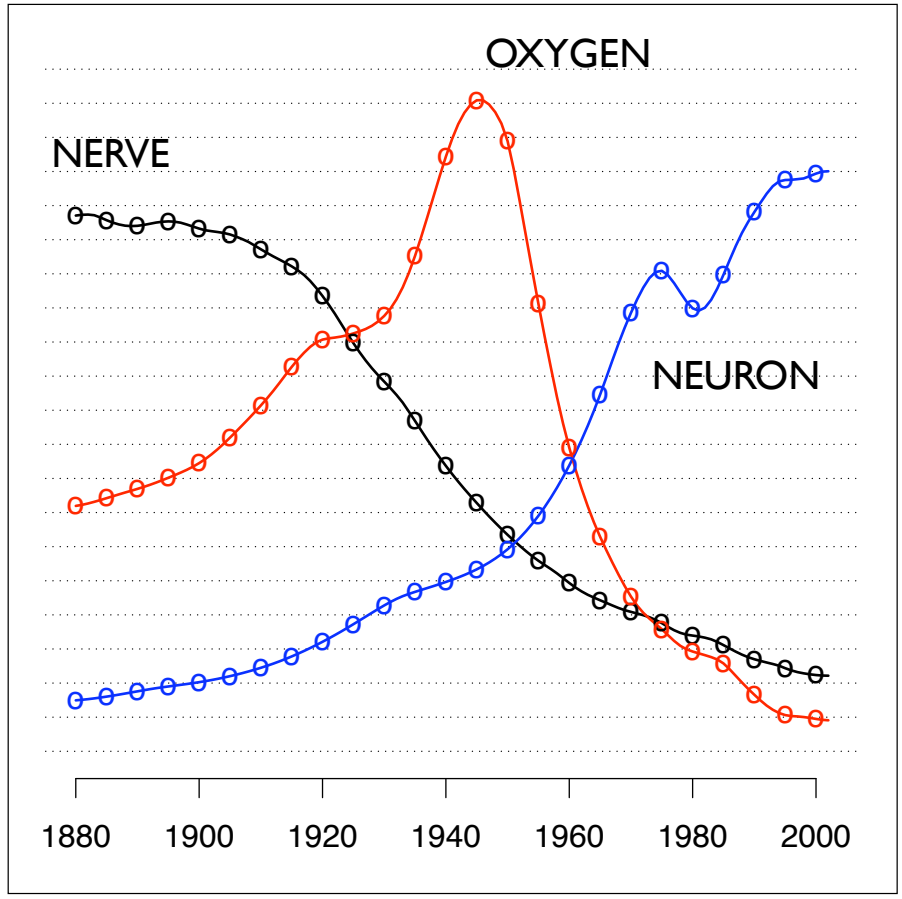
1. **Discover** the thematic structure
2. **Annotate** the documents
3. **Use** the annotations to visualize, organize, summarize, ...

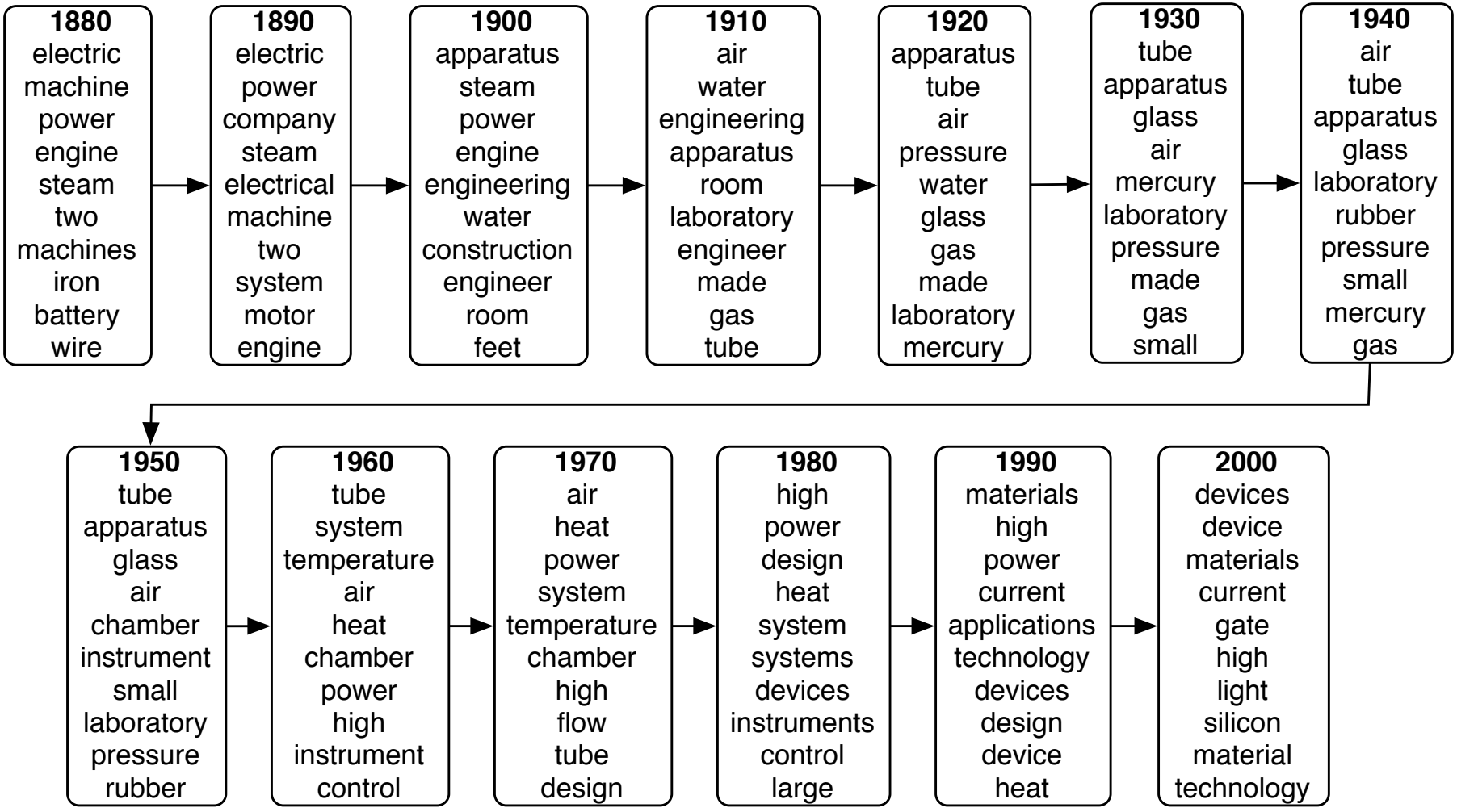

activated tyrosine phosphorylation activation phosphorylation kinase
p53 cell cycle activity cyclin regulation
proteins protein binding domain domains
brain memory subjects left task
neurons stimulus motor visual cortical
synapses ltp glutamate synaptic neurons
surface tip image sample device
rna dna rna polymerase cleavage site
computer problem information computers problems
materials organic polymer polymers molecules
research funding support nih program
science scientists says research people
receptor receptors ligand ligands apoptosis
amino acids cdna sequence isolated protein
laser optical light electrons quantum
physicists particles physics particle experiment
sequence sequences genome dna sequencing
surface liquid surfaces fluid model
wild type mutant mutations mutants mutation
enzyme enzymes iron active site reduction
reaction reactions molecule molecules transition state
stars astronomers universe galaxies galaxy
united states women universities students education
cells cell expression cell lines bone marrow
plants plant gene genes arabidopsis
magnetic magnetic field spin superconductivity superconducting
pressure high pressure pressures core inner core
mantle crust upper mantle meteorites ratios
sun solar wind earth planets planet
bacteria bacterial host resistance parasite
development embryos drosophila genes expression
fossil record birds fossils dinosaurs fossil
mice antigen t cells antigens immune response
virus hiv aids infection viruses
gene disease mutations families mutation
species forest forests populations ecosystems
earthquake earthquakes fault images data
co2 carbon carbon dioxide methane water
patients disease treatment drugs clinical
cells proteins researchers protein found
genetic population populations differences variation
ancient found impact million years ago africa
volcanic deposits magma eruption volcanism
climate ocean ice changes climate change
ozone atmospheric measurements stratosphere concentrations

"Theoretical Physics"



"Neuroscience"




1880
electric
machine
power
engine
steam
two
machines
iron
battery
wire
1890
electric
power
company
steam
electrical
machine
two
system
motor
engine
1900
apparatus
steam
power
engine
engineering
water
construction
engineer
room
feet
1910
air
water
engineering
apparatus
room
laboratory
engineer
made
gas
tube
1920
apparatus
tube
air
pressure
water
glass
gas
made
laboratory
mercury
1930
tube
apparatus
glass
air
mercury
laboratory
pressure
made
gas
small
1940
air
tube
apparatus
glass
laboratory
rubber
pressure
small
mercury
gas
1950
tube
apparatus
glass
air
chamber
instrument
small
laboratory
pressure
rubber
1960
tube
system
temperature
air
heat
chamber
power
high
instrument
control
1970
air
heat
power
system
temperature
chamber
high
flow
tube
design
1980
high
power
design
heat
system
systems
devices
instruments
control
large
1990
materials
high
power
current
applications
technology
devices
design
device
heat
2000
devices
device
materials
current
gate
high
light
silicon
material
technology

SKY WATER TREE
MOUNTAIN PEOPLE

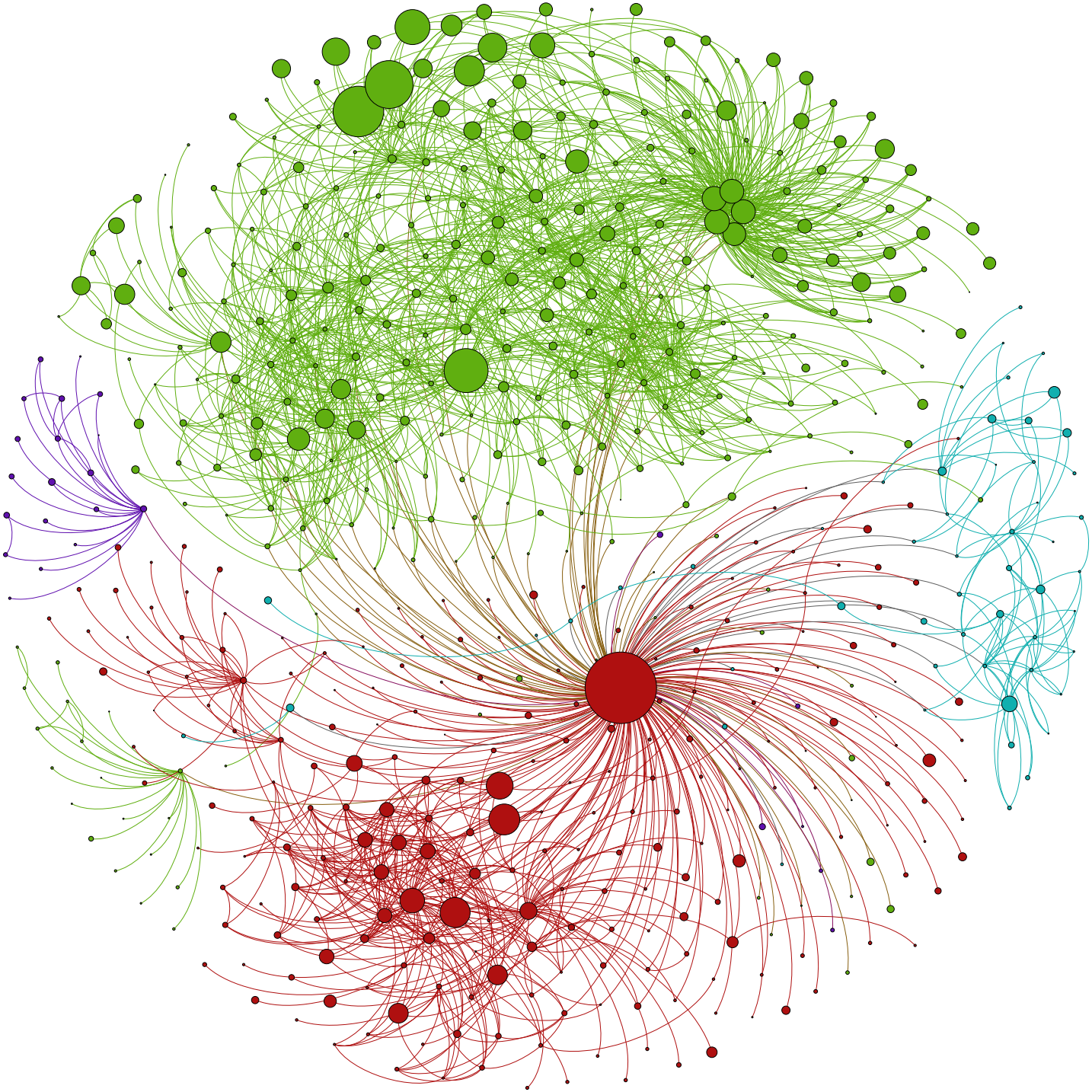
SCOTLAND WATER
FLOWER HILLS TREE

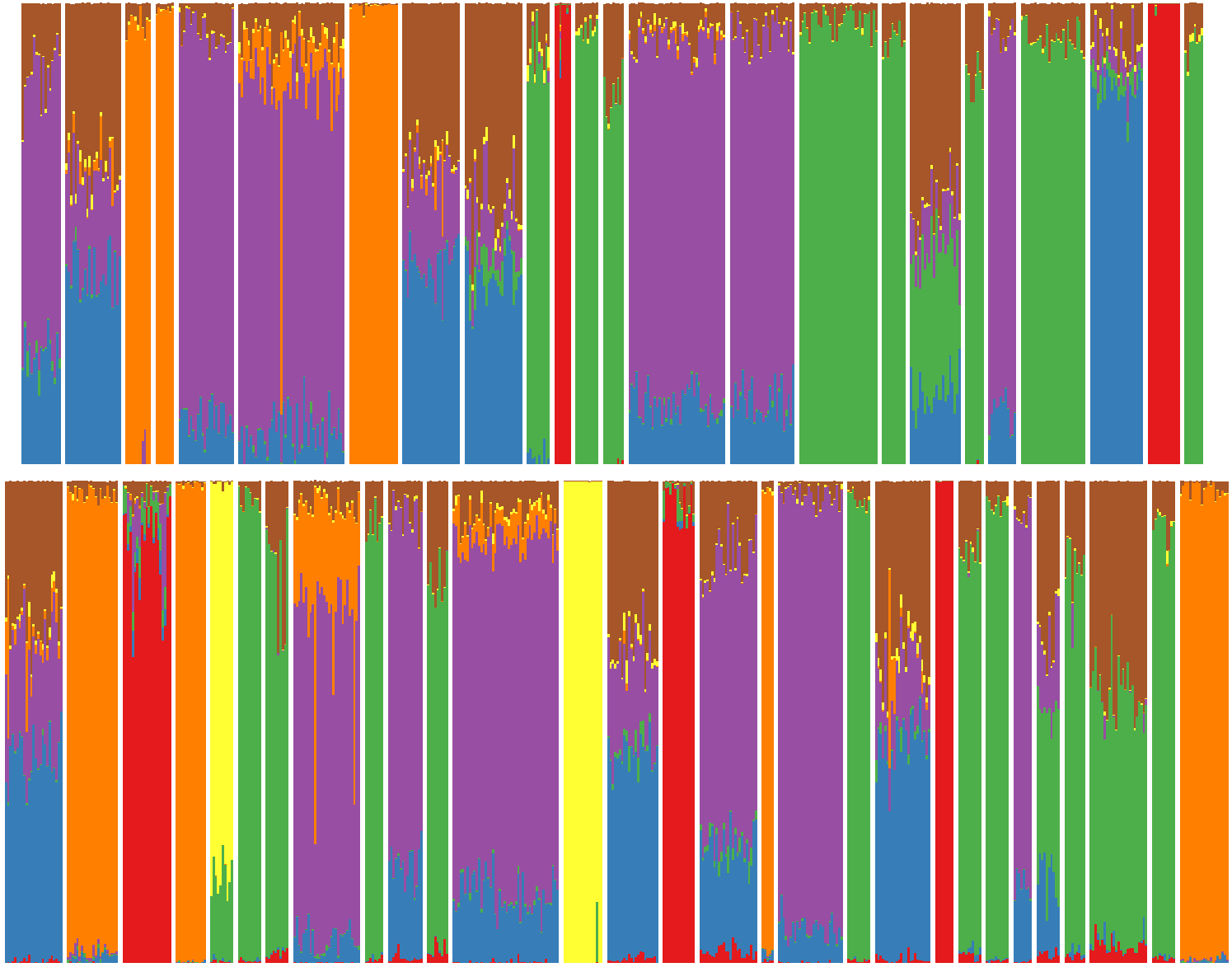
SKY WATER BUILDING
PEOPLE WATER

FISH WATER OCEAN
TREE CORAL

PEOPLE MARKET PATTERN
TEXTILE DISPLAY

BIRDS NEST TREE
BRANCH LEAVES





Charles Darwin's library

The NYC subway

- **People read documents.**
- These might be people for whom we want to form predictions.
- And, their behavior is an additional signal about the meaning of the documents and the organization of the collection.

This talk

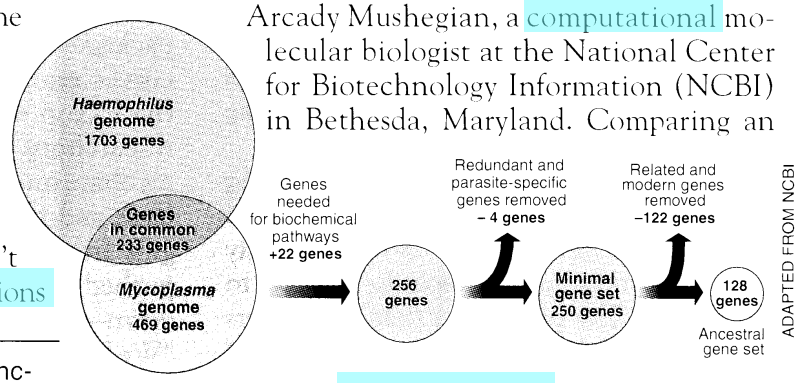
1. Introduction to topic modeling
2. Recommendation and exploration with collaborative topic models
3. The bigger picture: Using probability models to solve problems with data

Introduction to Topic Modeling

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Documents exhibit multiple topics.

Topics

gene	0.04
dna	0.02
genetic	0.01
...	

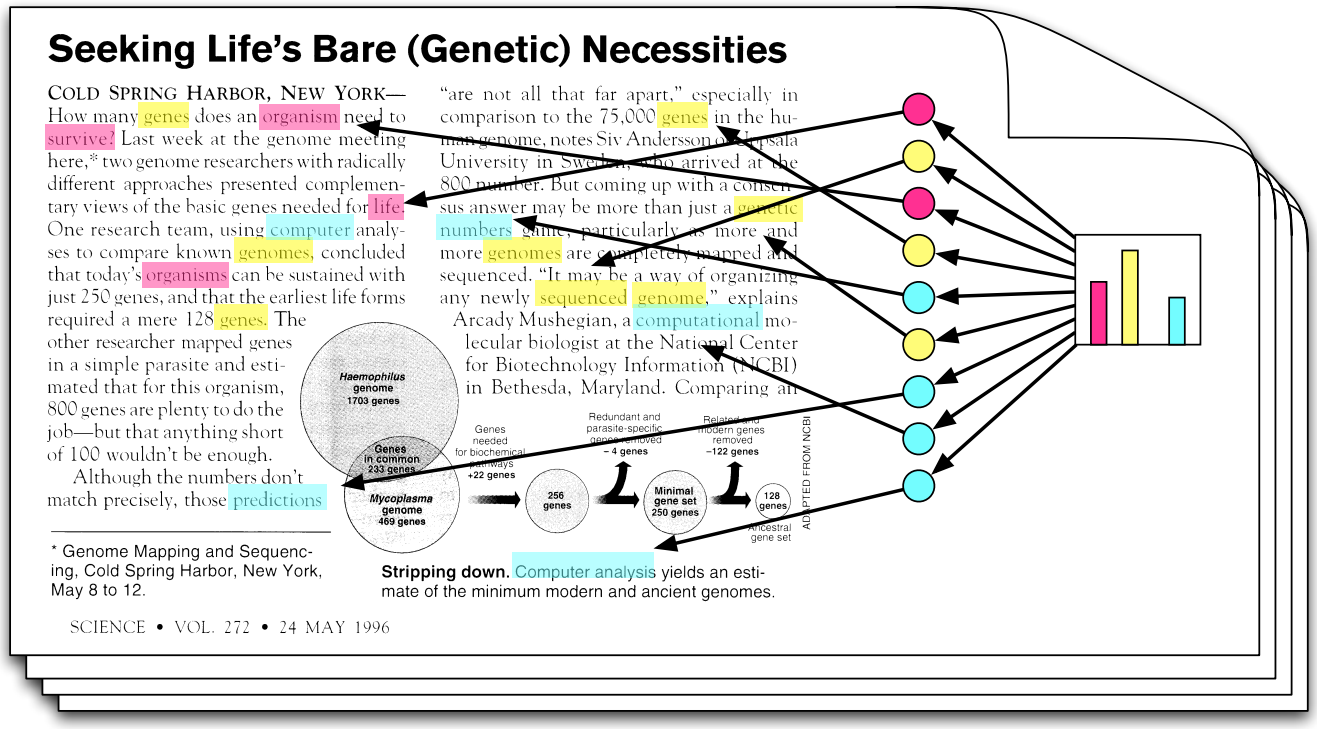
life	0.02
evolve	0.01
organism	0.01
...	

brain	0.04
neuron	0.02
nerve	0.01
...	

data	0.02
number	0.02
computer	0.01
...	

Documents

Topic proportions and assignments



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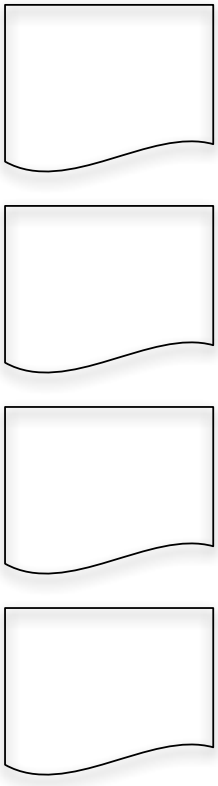
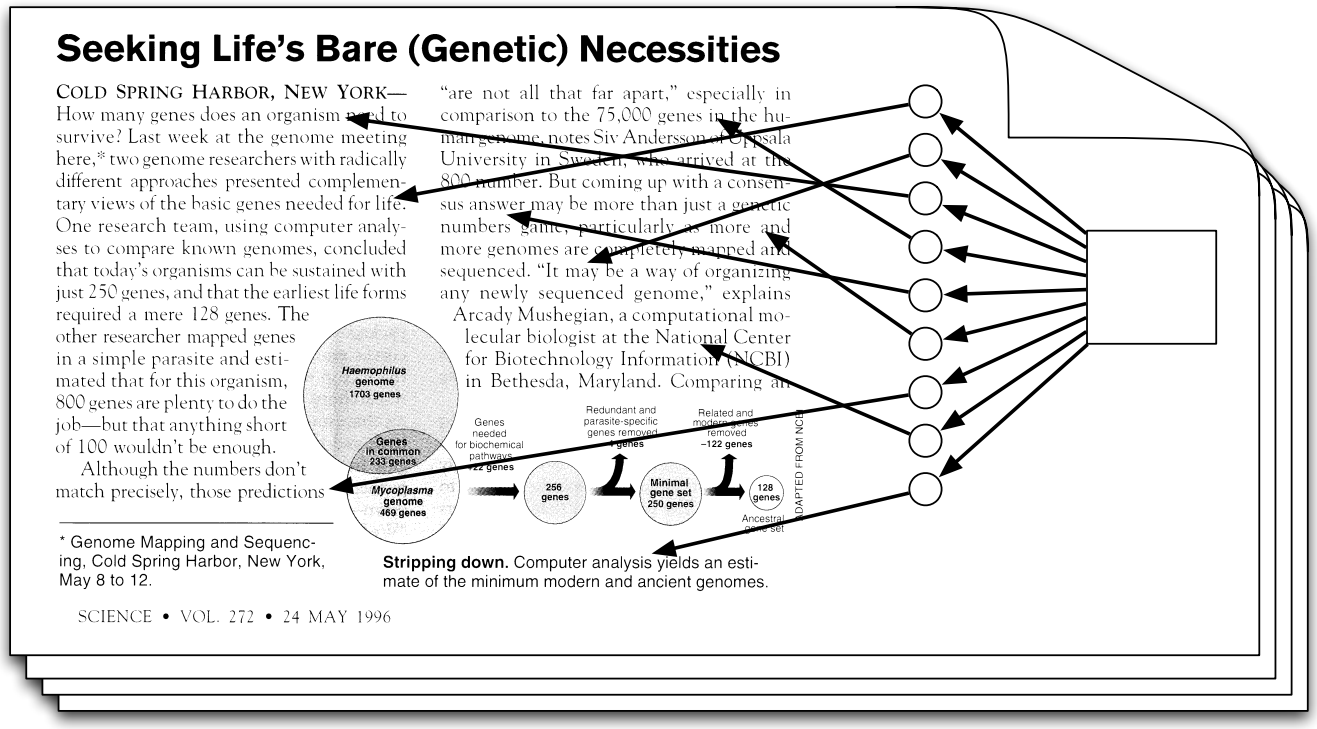
Latent Dirichlet Allocation

Topics

Documents

Topic proportions and assignments





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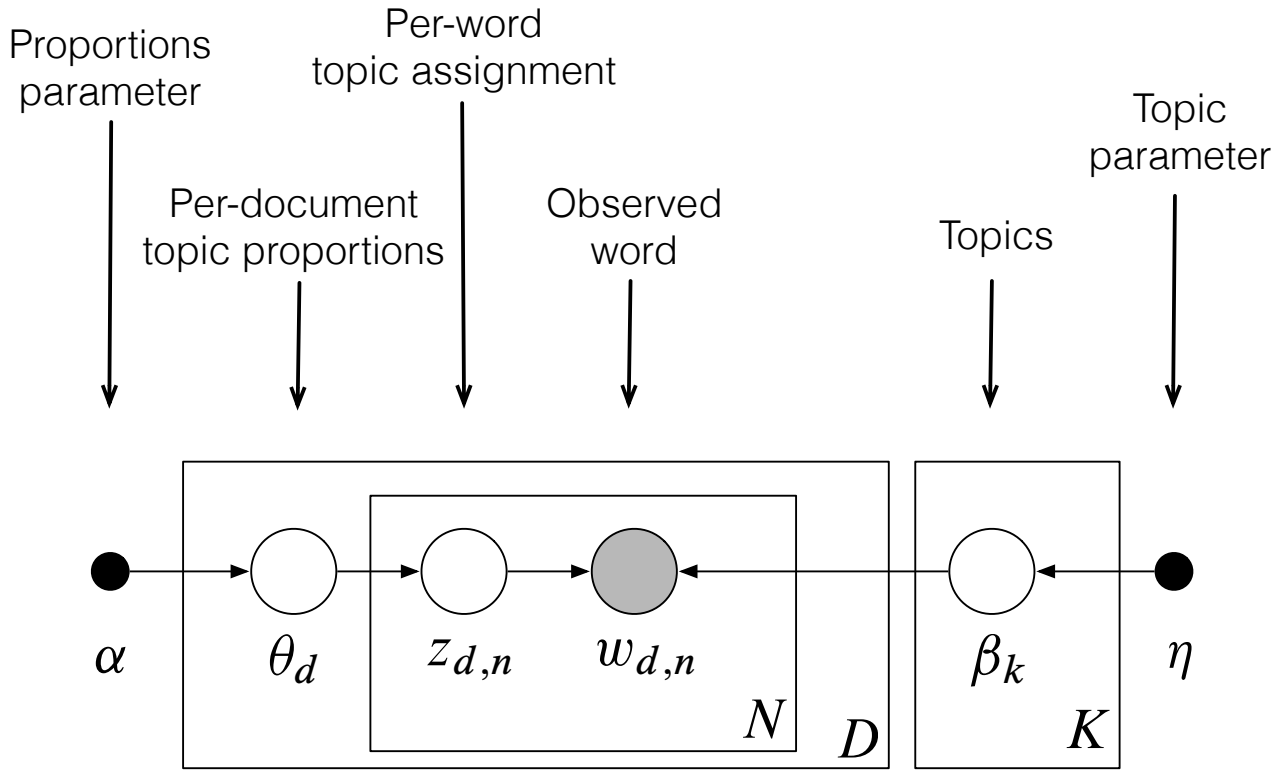
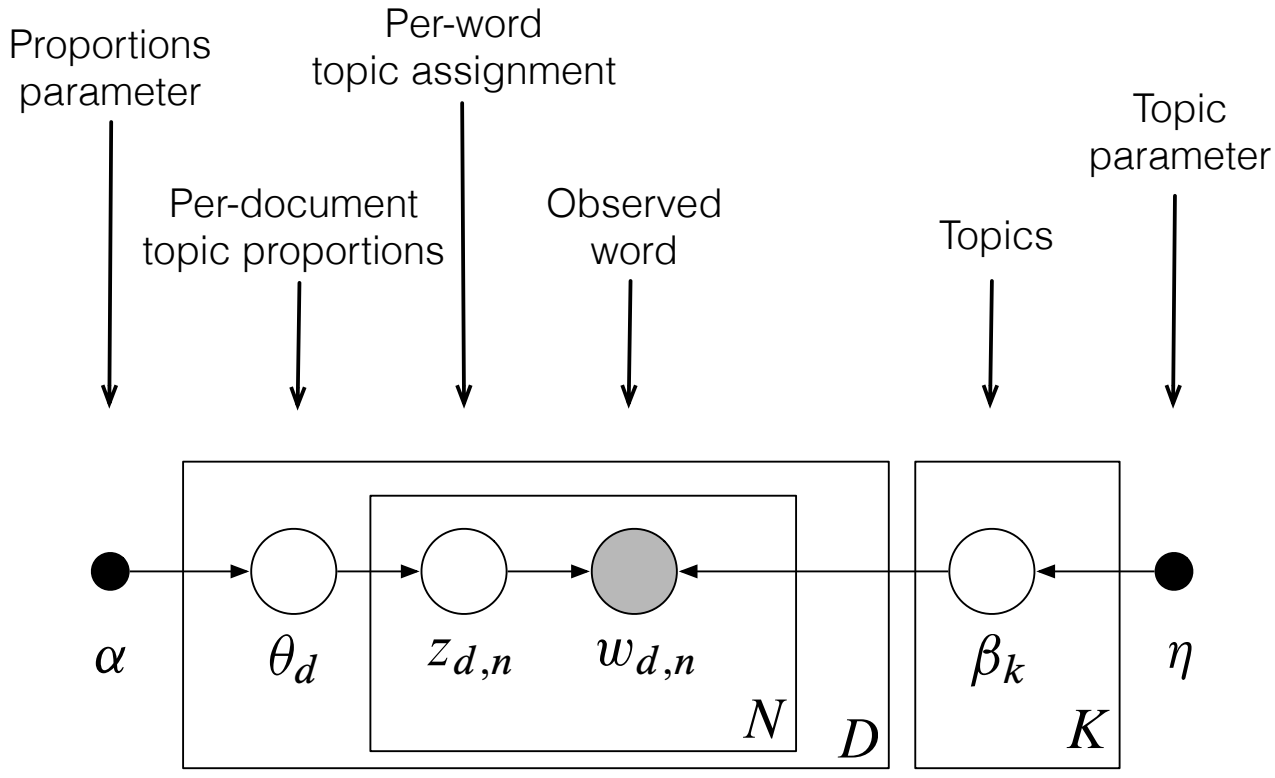


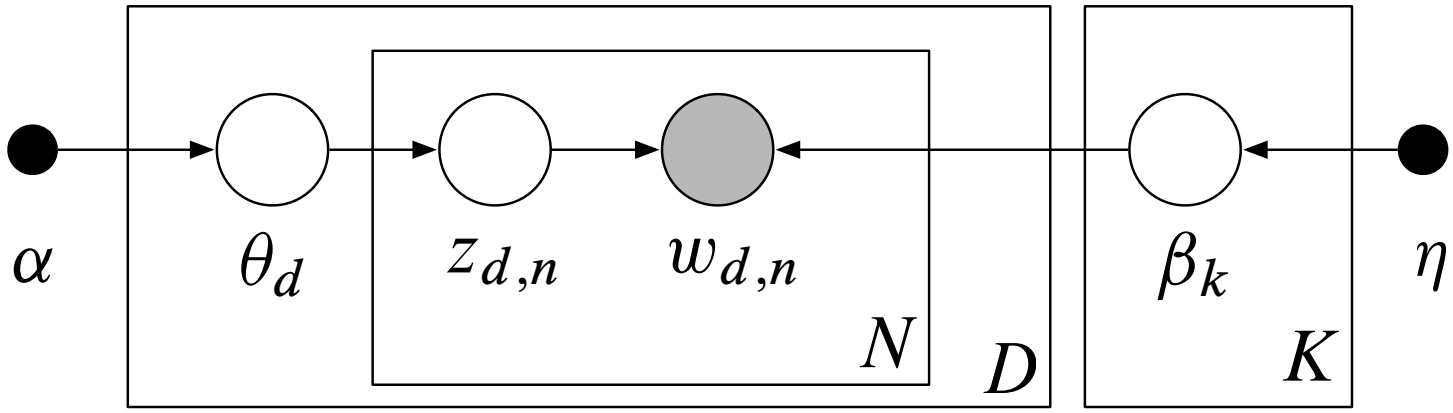
LDA as a graphical model

- Nodes are random variables; edges indicate dependence.
- Shaded nodes are observed; unshaded nodes are hidden.
- Plates indicate replicated variables.

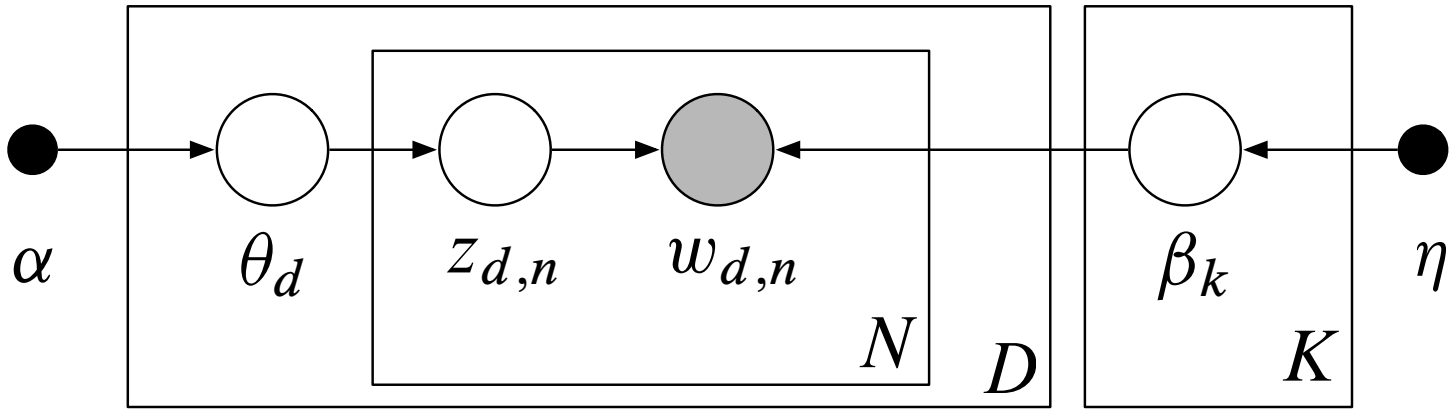


LDA as a graphical model

- Encodes independence assumptions about the variables
- Defines a factorization of the joint probability distribution
- Connects to algorithms for computing with data



- The joint defines a posterior, $p(\theta, z, \beta \mid w)$.
- From a collection of documents, infer
  - Per-word topic assignment $z_{d,n}$
  - Per-document topic proportions θ_d
  - Per-corpus topic distributions β_k
- Then use posterior expectations to perform the task at hand: information retrieval, document similarity, exploration, and others.



- Mean field variational methods (Blei et al., 2001, 2003)
- Expectation propagation (Minka and Lafferty, 2002)
- Collapsed Gibbs sampling (Griffiths and Steyvers, 2002)
- Distributed sampling (Newman et al., 2008; Ahmed et al., 2012)
- Collapsed variational inference (Teh et al., 2006)
- Stochastic inference (Hoffman et al., 2010, 2013; Mimno et al., 2012)
- Factorization inference (Arora et al., 2012; Anandkumar et al., 2012)

- **Data**: The OCR'ed collection of *Science* from 1990–2000
  - 17K documents
  - 11M words
  - 20K unique terms (stop words and rare words removed)
- **Model**: 100-topic LDA model using variational inference.

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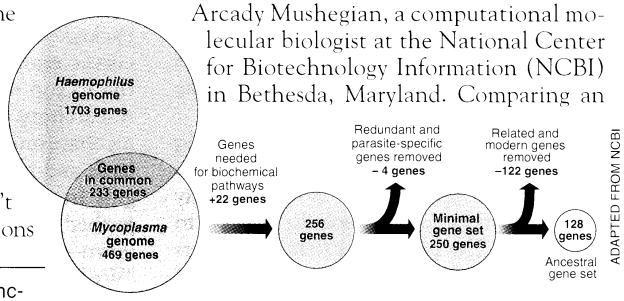

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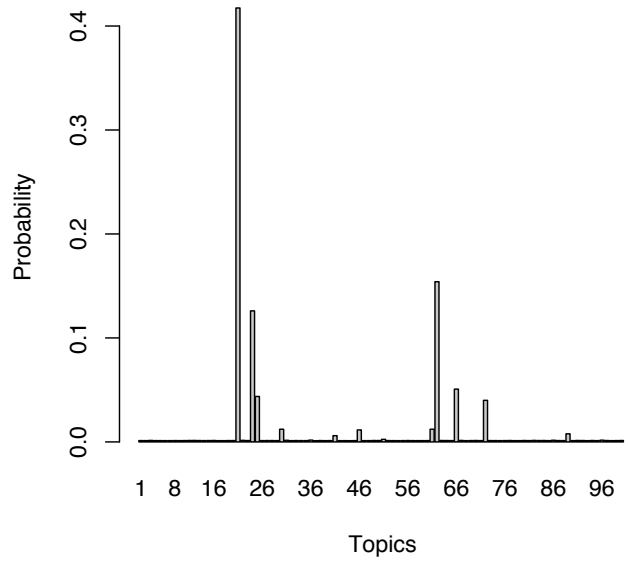


human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

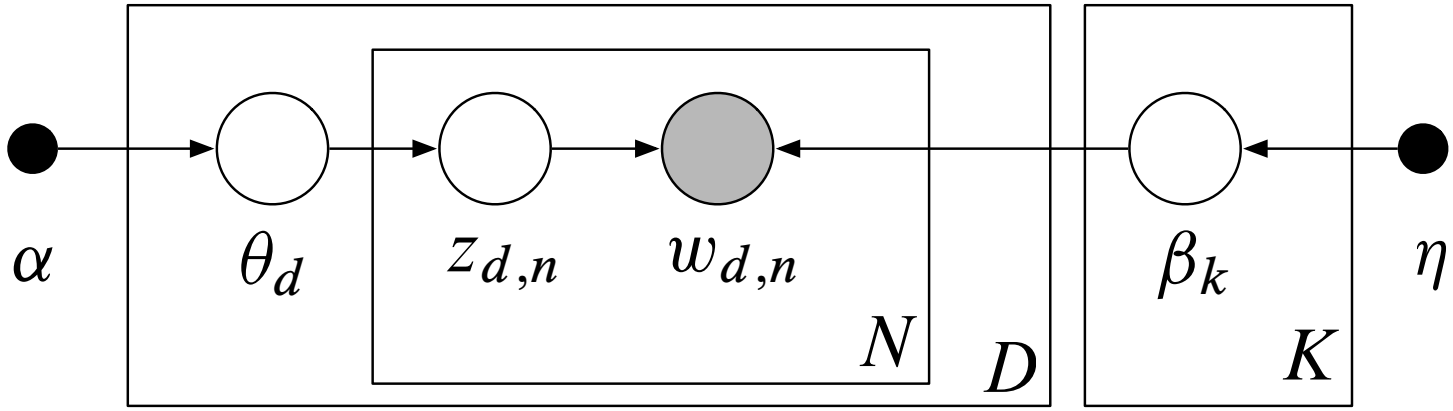
1	2	3	4	5
Game	Life	Film	Book	Wine
Season	Know	Movie	Life	Street
Team	School	Show	Books	Hotel
Coach	Street	Life	Novel	House
Play	Man	Television	Story	Room
Points	Family	Films	Man	Night
Games	Says	Director	Author	Place
Giants	House	Man	House	Restaurant
Second	Children	Story	War	Park
Players	Night	Says	Children	Garden

6	7	8	9	10
Bush	Building	Won	Yankees	Government
Campaign	Street	Team	Game	War
Clinton	Square	Second	Mets	Military
Republican	Housing	Race	Season	Officials
House	House	Round	Run	Iraq
Party	Buildings	Cup	League	Forces
Democratic	Development	Open	Baseball	Iraqi
Political	Space	Game	Team	Army
Democrats	Percent	Play	Games	Troops
Senator	Real	Win	Hit	Soldiers

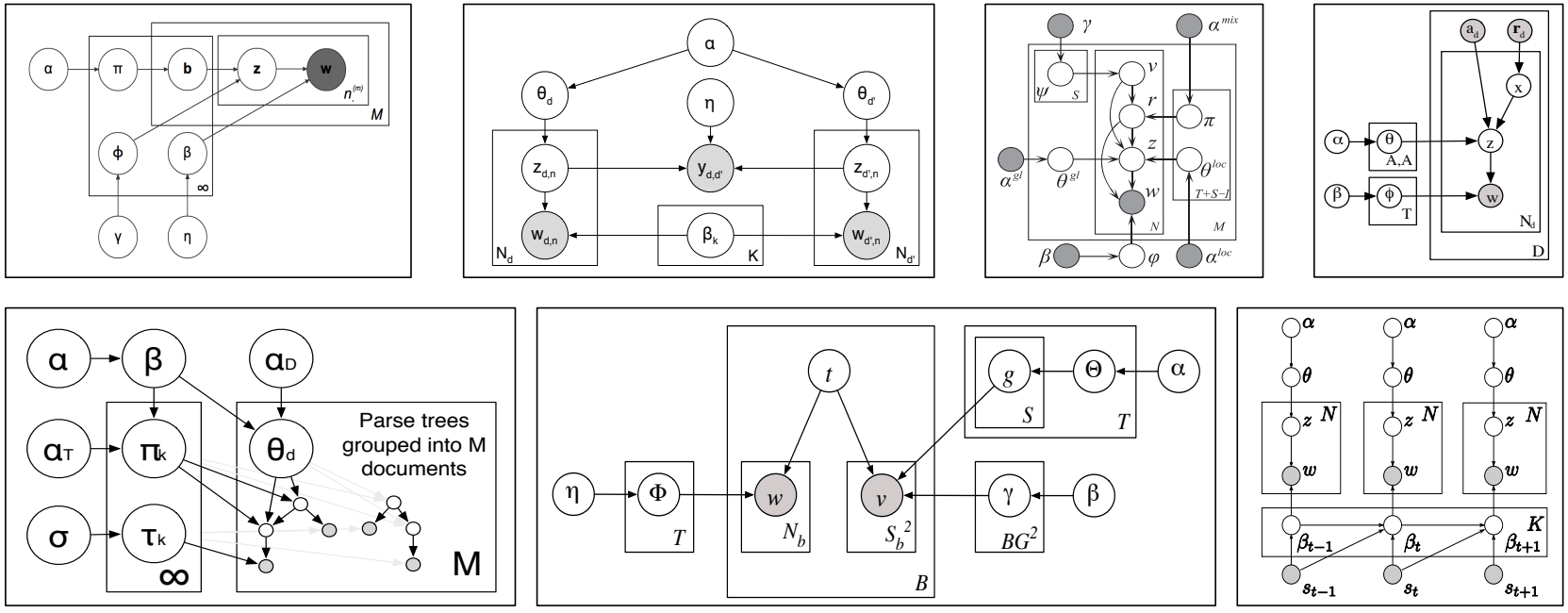
11	12	13	14	15
Children	Stock	Church	Art	Police
School	Percent	War	Museum	Yesterday
Women	Companies	Women	Show	Man
Family	Fund	Life	Gallery	Officer
Parents	Market	Black	Works	Officers
Child	Bank	Political	Artists	Case
Life	Investors	Catholic	Street	Found
Says	Funds	Government	Artist	Charged
Help	Financial	Jewish	Paintings	Street
Mother	Business	Pope	Exhibition	Shot

How does LDA "work"?

- LDA trades off two goals.
  1. In each **document**, allocate its words to **few topics**.
  2. In each **topic**, assign high probability to **few terms**.
- These goals are at odds.
  - Putting a document in a single topic makes #2 hard:
    All of its words must have probability under that topic.
  - Putting very few words in each topic makes #1 hard:
    To cover a document's words, it must assign many topics to it.
- Trading off these goals finds groups of tightly co-occurring words.



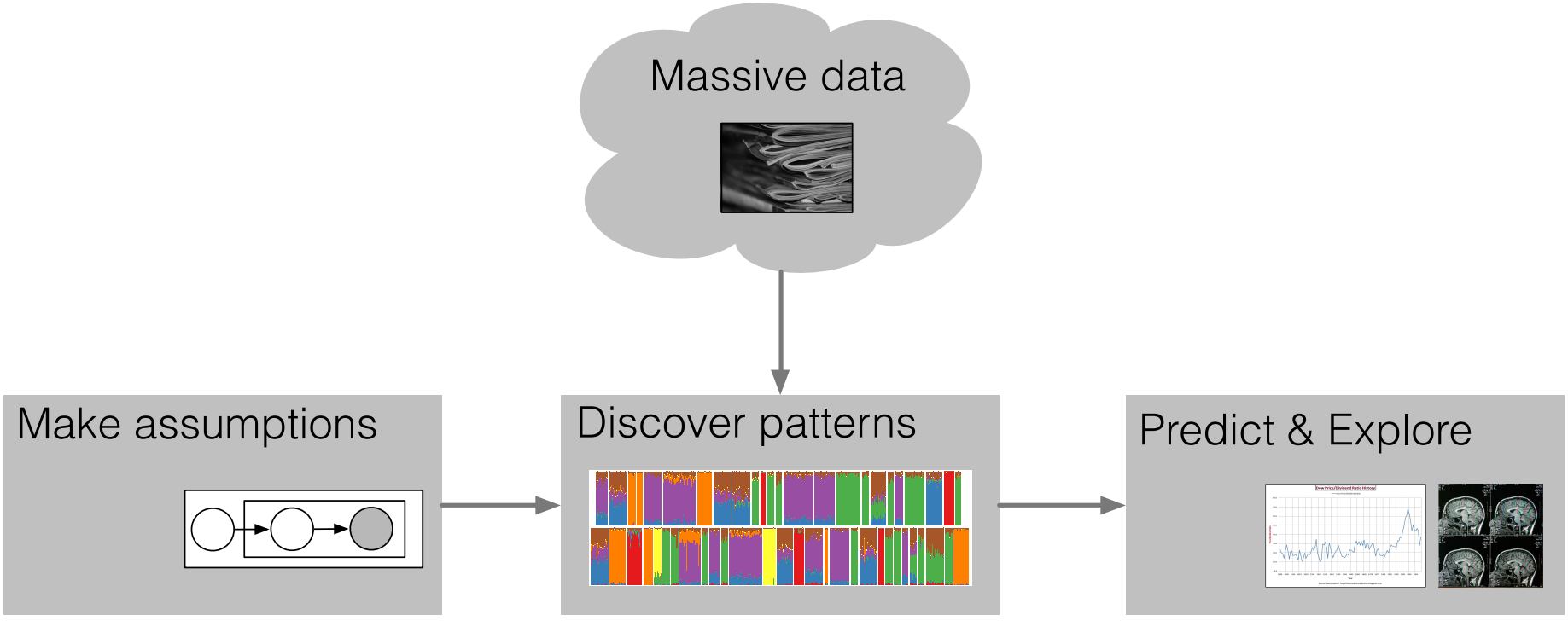
- LDA discovers themes through posterior inference.
- Other perspectives
  - Latent semantic analysis [Deerwester et al., 1990; Hofmann, 1999]
  - A mixed-membership model [Erosheva, 2004]
  - PCA and matrix factorization [Jakulin and Buntine, 2002]
  - Was independently invented for genetics [Pritchard et al., 2000]



- Topic modeling is an active field of research.
  LDA is a simple building block that enables many applications.

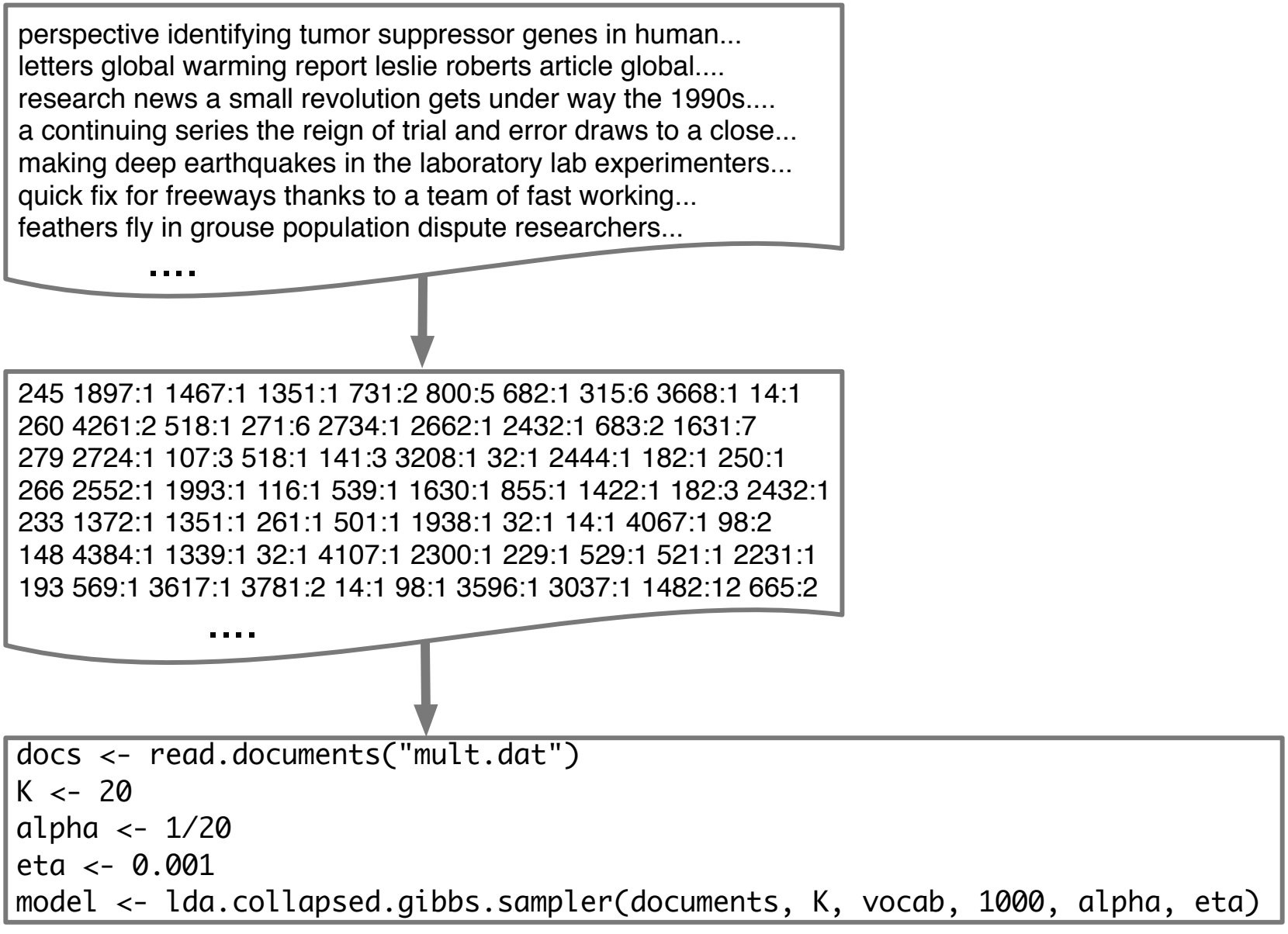
- Organizing and finding patterns in text has become important in the sciences, humanties, industry, and culture.

- Algorithmic improvements let us fit models to massive data.
  (See VW, Gensim, Mallet, others.)



- Case study in **text analysis with probability models**
- Topic modeling research
  - develops new models.
  - develops new inference algorithms.
  - develops new applications, visualizations, tools.

Quick diversion: Fitting a topic model in your spare time


perspective identifying tumor suppressor genes in human...
letters global warming report leslie roberts article global....
research news a small revolution gets under way the 1990s....
a continuing series the reign of trial and error draws to a close...
making deep earthquakes in the laboratory lab experimenters...
quick fix for freeways thanks to a team of fast working...
feathers fly in grouse population dispute researchers...
....
245 1897:1 1467:1 1351:1 731:2 800:5 682:1 315:6 3668:1 14:1
260 4261:2 518:1 271:6 2734:1 2662:1 2432:1 683:2 1631:7
279 2724:1 107:3 518:1 141:3 3208:1 32:1 2444:1 182:1 250:1
266 2552:1 1993:1 116:1 539:1 1630:1 855:1 1422:1 182:3 2432:1
233 1372:1 1351:1 261:1 501:1 1938:1 32:1 14:1 4067:1 98:2
148 4384:1 1339:1 32:1 4107:1 2300:1 229:1 529:1 521:1 2231:1
193 569:1 3617:1 3781:2 14:1 98:1 3596:1 3037:1 1482:12 665:2
....
docs <- read.documents("mult.dat")
K <- 20
alpha <- 1/20
eta <- 0.001
model <- lda.collapsed.gibbs.sampler(documents, K, vocab, 1000, alpha, eta)

LDA in R


1
dna
gene
sequence
genes
sequences
human
genome
genetic
analysis
two
2
protein
cell
cells
proteins
receptor
fig
binding
activity
activation
kinase
3
water
climate
atmospheric
temperature
global
surface
ocean
carbon
atmosphere
changes
4
says
researchers
new
university
just
science
like
work
first
years
5
mantle
high
earth
pressure
seismic
crust
temperature
earths
lower
earthquakes
6
end
article
start
science
readers
service
news
card
circle
letters
7
time
data
two
model
fig
system
number
different
results
rate
8
materials
surface
high
structure
temperature
molecules
chemical
molecular
fig
university
9
dna
rna
transcription
protein
site
binding
sequence
proteins
specific
sequences
10
disease
cancer
patients
human
gene
medical
studies
drug
normal
drugs
11
years
million
ago
age
university
north
early
fig
evidence
record
12
species
evolution
population
evolutionary
university
populations
natural
studies
genetic
biology
13
protein
structure
proteins
two
amino
binding
acid
residues
molecular
structural
14
cells
cell
virus
hiv
infection
immune
human
antigen
infected
viral
15
space
solar
observations
earth
stars
university
mass
sun
astronomers
telescope
16
fax
manager
science
aaas
advertising
sales
member
recruitment
associate
washington
17
cells
cell
gene
genes
expression
development
mutant
mice
fig
biology
18
energy
electron
state
light
quantum
physics
electrons
high
laser
magnetic
19
research
science
national
scientific
scientists
new
states
university
united
health
20
neurons
brain
cells
activity
fig
channels
university
cortex
neuronal
visual

Wikipedia Topics

Relative Presence of Topics in all Documents

{household, population, female}
{film, series, show}
{theory, work, human}
{son, year, death}
{war, force, army}
{system, computer, user}
{album, band, music}
{government, party, election}
{game, team, player}
{god, call, give}
{company, market, business}
{math, number, function}
{city, large, area}

{film, series, show}

words	related documents	related topics
film	The X-Files	{son, year, death}
series	Orson Welles	{work, book, publish}
show	Stanley Kubrick	{album, band, music}
character	B movie	{woman, child, man}
play	Mystery Science Theater 3000	{law, state, case}
make	Monty Python	{black, white, people}
episode	Doctor Who	{theory, work, human}
movie	Sam Peckinpah	{@card@, make, design}
good	Married... with Children	{war, force, army}
release	History of film	{god, call, give}
feature	The A-Team	{game, team, player}
television	Pulp Fiction (film)	{day, year, event}
star	Mad (magazine)	{company, market, business}

Stanley Kubrick

related topics

{film, series, show}
{theory, work, human}
{son, year, death}
{black, white, people}
{god, call, give}
{math, energy, light}

Stanley Kubrick (July 26, 1928 – March 7, 1999) was an American film director, writer, producer, and photographer who lived in England during most of the last four decades of his career. Kubrick was noted for the scrupulous care with which he chose his subjects, his slow method of working, the variety of genres he worked in, his technical perfectionism, and his reclusiveness about his films and personal life. He worked far beyond the confines of the Hollywood system, maintaining almost complete artistic control and making movies according to his own whims and time constraints, but with the rare advantage of big-studio financial support for all his endeavors.

Kubrick's films are characterized by a formal visual style and meticulous attention to detail—his later films often have elements of surrealism and expressionism that eschews structured linear narrative. His films are repeatedly described as slow and methodical, and are often perceived as a reflection of his obsessive and perfectionist nature.[1] A recurring theme in his films is man's inhumanity to man. While often viewed as

related documents

Orson Welles
B movie
Mystery Science Theater 3000
Monty Python
Doctor Who
Sam Peckinpah
The A-Team
Pulp Fiction (film)
Buffy the Vampire Slayer (TV series)
The X-Files
Sunset Boulevard (film)
Jack Benny

{theory, work, human}

words	related documents	related topics
theory	Meme	{work, book, publish}
work	Intelligent design	{law, state, case}
human	Immanuel Kant	{son, year, death}
idea	Philosophy of mathematics	{woman, child, man}
term	History of science	{god, call, give}
study	Free will	{black, white, people}
view	Truth	{film, series, show}
science	Psychoanalysis	{war, force, army}
concept	Charles Peirce	{language, word, form}
form	Existentialism	{@card@, make, design}
world	Deconstruction	{church, century, christian}
argue	Social sciences	{rate, high, increase}
social	Idealism	{company, market, business}

Collaborative Topic Models

with Prem Gopalan, Laurent Charlin, and Chong Wang

Charles Darwin's library

Reading on the New York subway

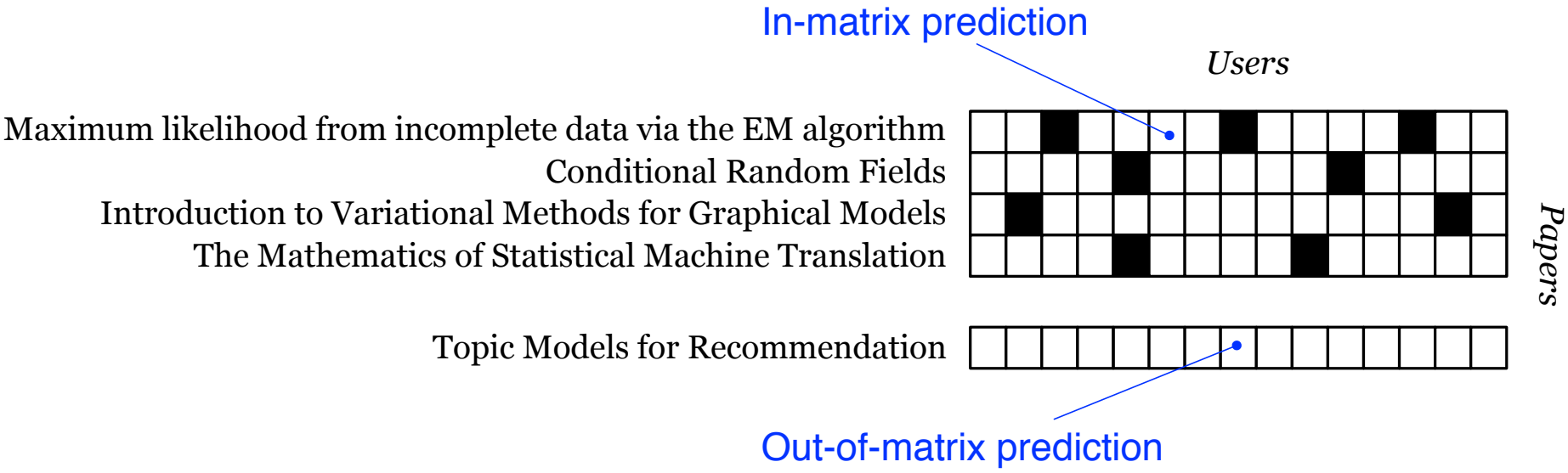
- **People read documents.**
- *Collaborative topic models* connect content to consumption

Exploration and Exploitation of Victorian Science in Darwin's Reading Notebooks

Jaimie Murdock[1,2], Colin Allen[1,3,4], and Simon DeDeo*[1,2,5]

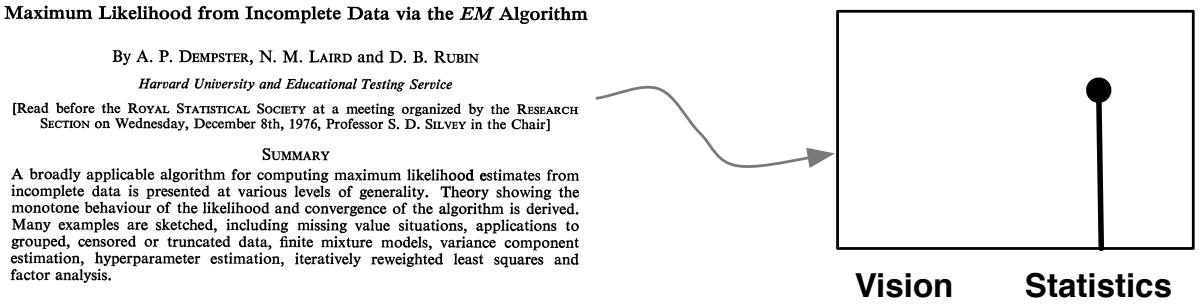
[1]Program in Cognitive Science, Indiana University, Bloomington, IN 47405, USA
[2]School of Informatics and Computing, Indiana University, Bloomington, IN 47405, USA
[3]Department of History and Philosophy of Science and Medicine, Indiana University, Bloomington, IN 47405, USA
[4]School of Humanities and Social Sciences, Xi'an Jiaotong University, Xi'an, China
[5]Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501, USA

September 25, 2015



- Example: Scientists share their research libraries.
- Collaborative topic models can
  - Helps readers discover documents
  - Describe readers in terms of topical preferences
  - Identify impactful, interdisciplinary articles

- Consider EM (Dempster et al., 1977). We infer topics from its text:



Maximum Likelihood from Incomplete Data via the *EM* Algorithm

By A. P. Dempster, N. M. Laird and D. B. Rubin

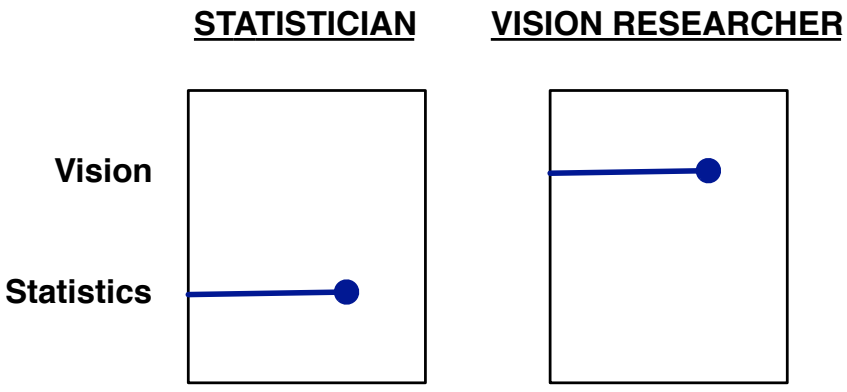
Harvard University and Educational Testing Service

[Read before the Royal Statistical Society at a meeting organized by the Research Section on Wednesday, December 8th, 1976, Professor S. D. Silvey in the Chair]

Summary

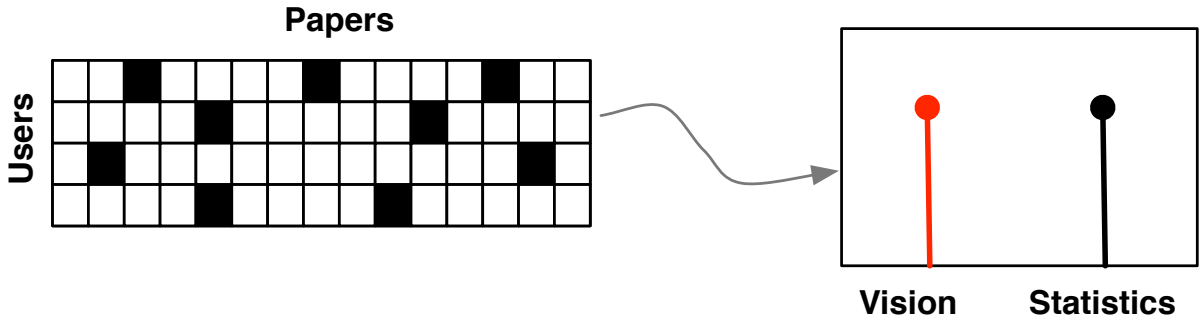
A broadly applicable algorithm for computing maximum likelihood estimates from incomplete data is presented at various levels of generality. Theory showing the monotone behaviour of the likelihood and convergence of the algorithm is derived. Many examples are sketched, including missing value situations, applications to grouped, censored or truncated data, finite mixture models, variance component estimation, hyperparameter estimation, iteratively reweighted least squares and factor analysis.

- Suppose there are two types of scientists

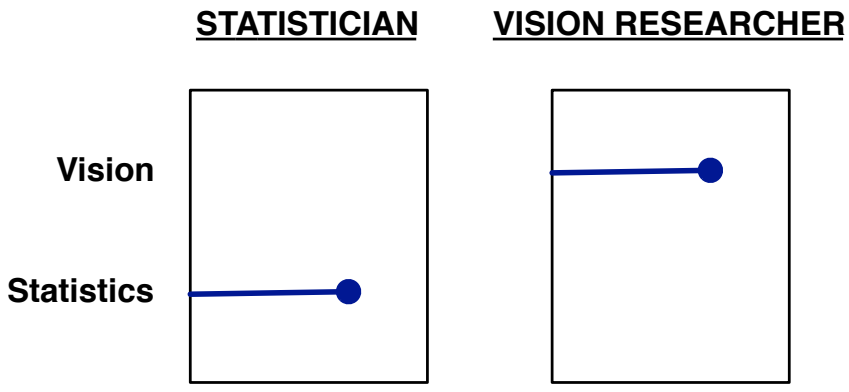


- We first recommend the EM paper to **statisticians**.

- With user data, we can adjust the topics to account for who liked it:



- Consider again the scientists



- We now recommend the EM paper to **vision researchers**.

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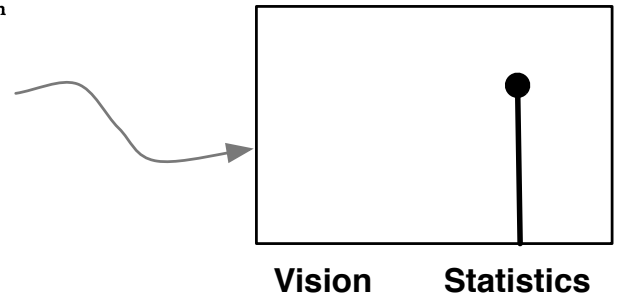
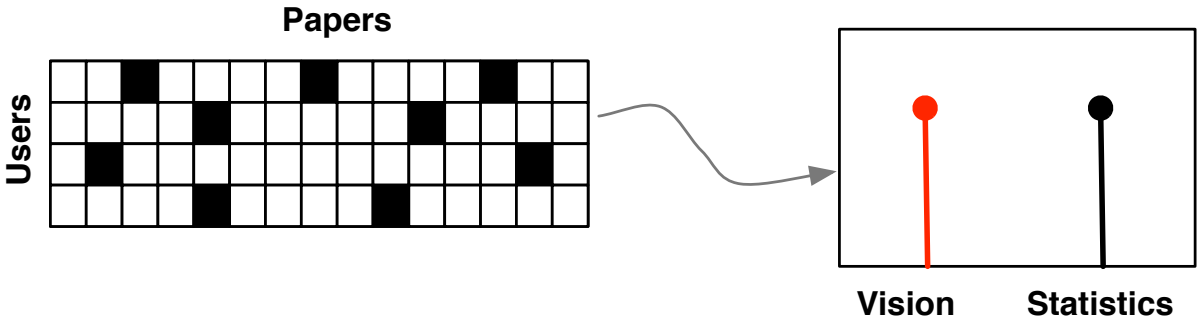
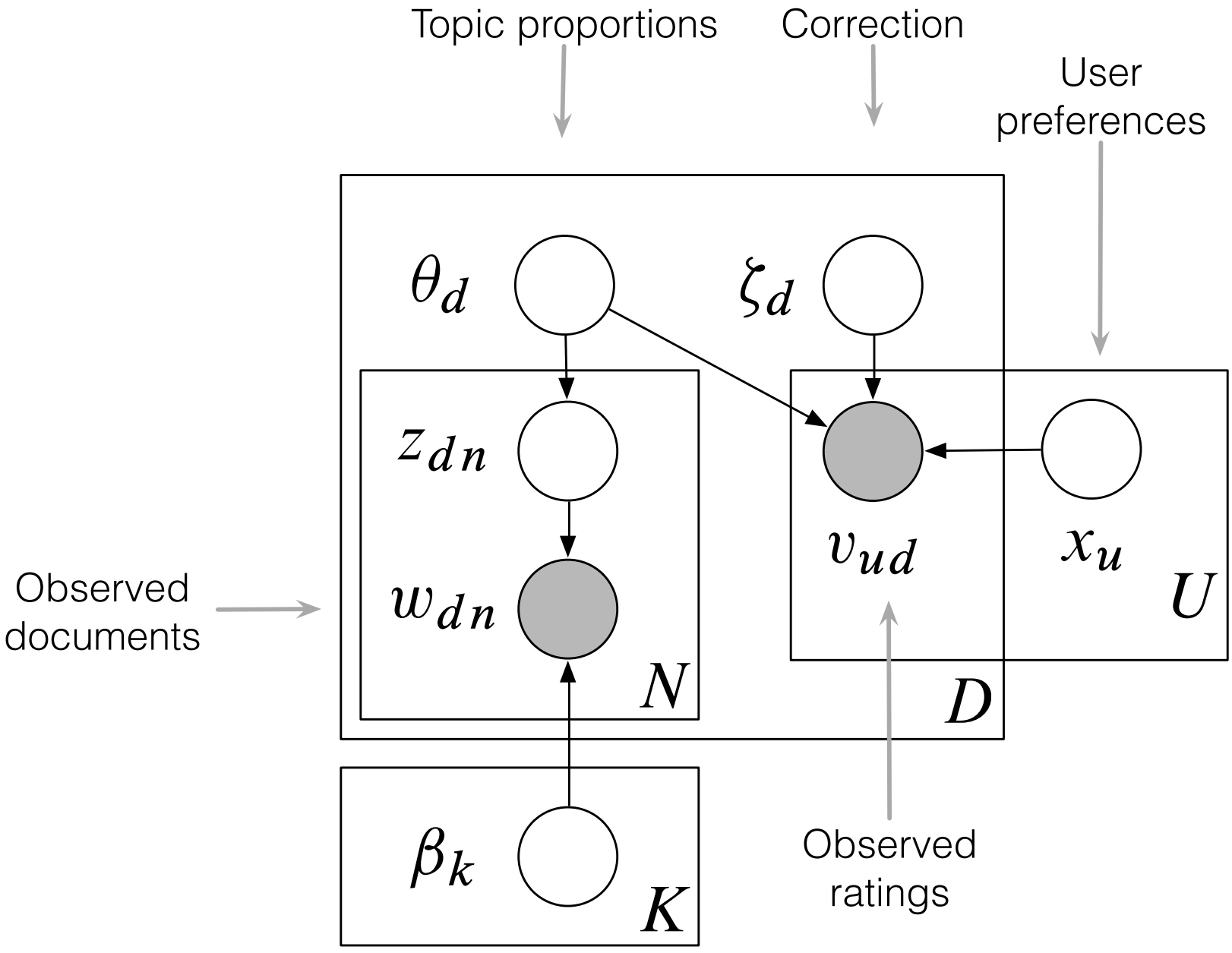
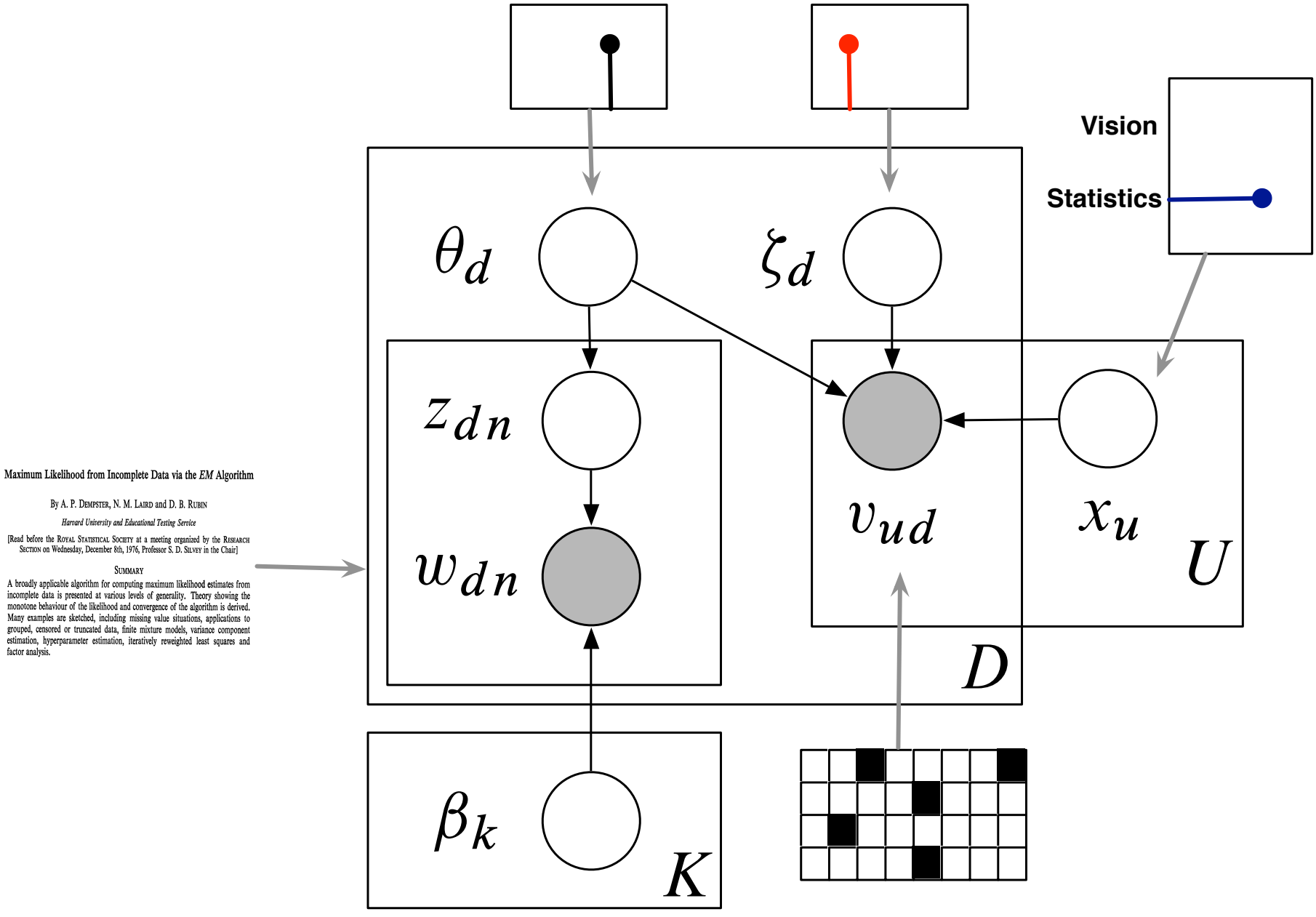




Without text, we cannot initially recommend to anyone.

Without user data, we cannot recommend to vision researchers.


Topic proportions
Correction
User preferences
θ_d
ζ_d
z_{dn}
v_{ud}
x_u
w_{dn}
N
D
U
Observed documents
β_k
K
Observed ratings



Maximum Likelihood from Incomplete Data via the *EM* Algorithm

By A. P. Dempster, N. M. Laird and D. B. Rubin

Harvard University and Educational Testing Service

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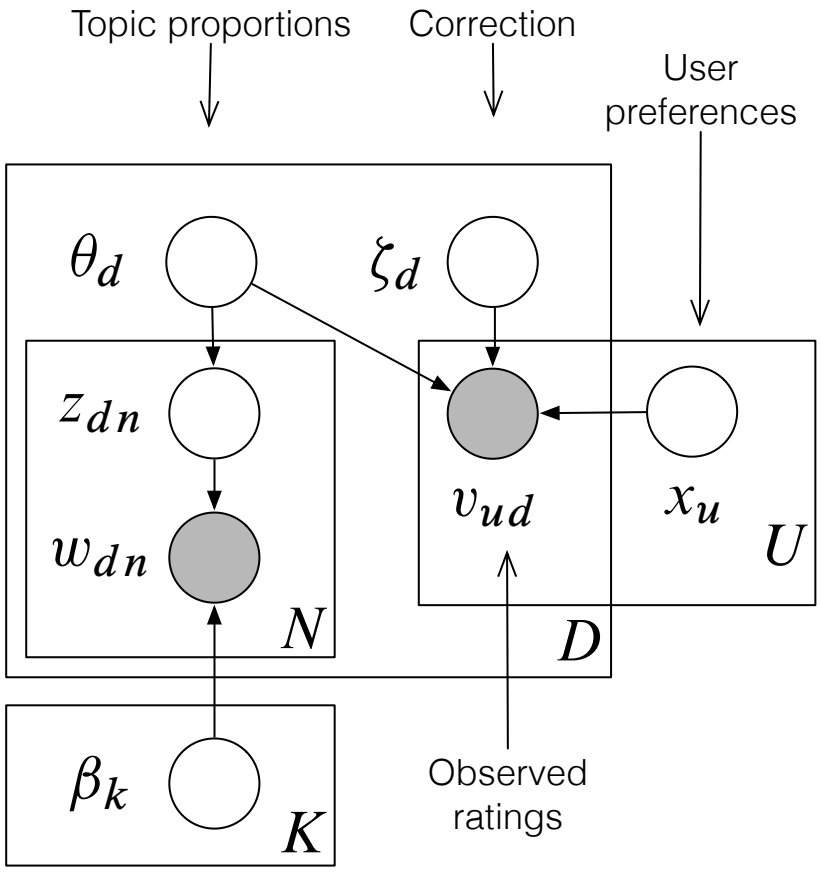

$$
\begin{aligned}
\theta_{dk} &\sim \text{Gamma}(\cdot,\cdot) \\
\zeta_{dk} &\sim \text{Gamma}(\cdot,\cdot) \\
x_{uk} &\sim \text{Gamma}(\cdot,\cdot) \\
v_{ud} &\sim \text{Poisson}((\theta_d + \zeta_d)^\top x_u)
\end{aligned}
$$

- Blends factorization-based and content-based recommendation
- Describes user preferences with interpretable topics
- Builds on Poisson factorization

  [Canney 2004; Dunson and Herring 2005; Gopalan et al. 2014)

- Big data set from Mendeley.com
- The data:
  - 261K documents
  - 80K users
  - 10K vocabulary terms
  - 25M observed words
  - 5.1M entries (sparsity is 0.02%)

- A decade of clicks on arXiv.org (2003–2013)
- The data:
  - 826K documents
  - 120K users
  - 14K vocabulary terms
  - 54M observed words
  - 43.6M entries (sparsity is 0.04%)

Maximum Likelihood from Incomplete Data via the *EM* Algorithm

By A. P. DEMPSTER, N. M. LAIRD and D. B. RUBIN

Harvard University and Educational Testing Service

[Read before the ROYAL STATISTICAL SOCIETY at a meeting organized by the RESEARCH SECTION on Wednesday, December 8th, 1976, Professor S. D. SILVEY in the Chair]

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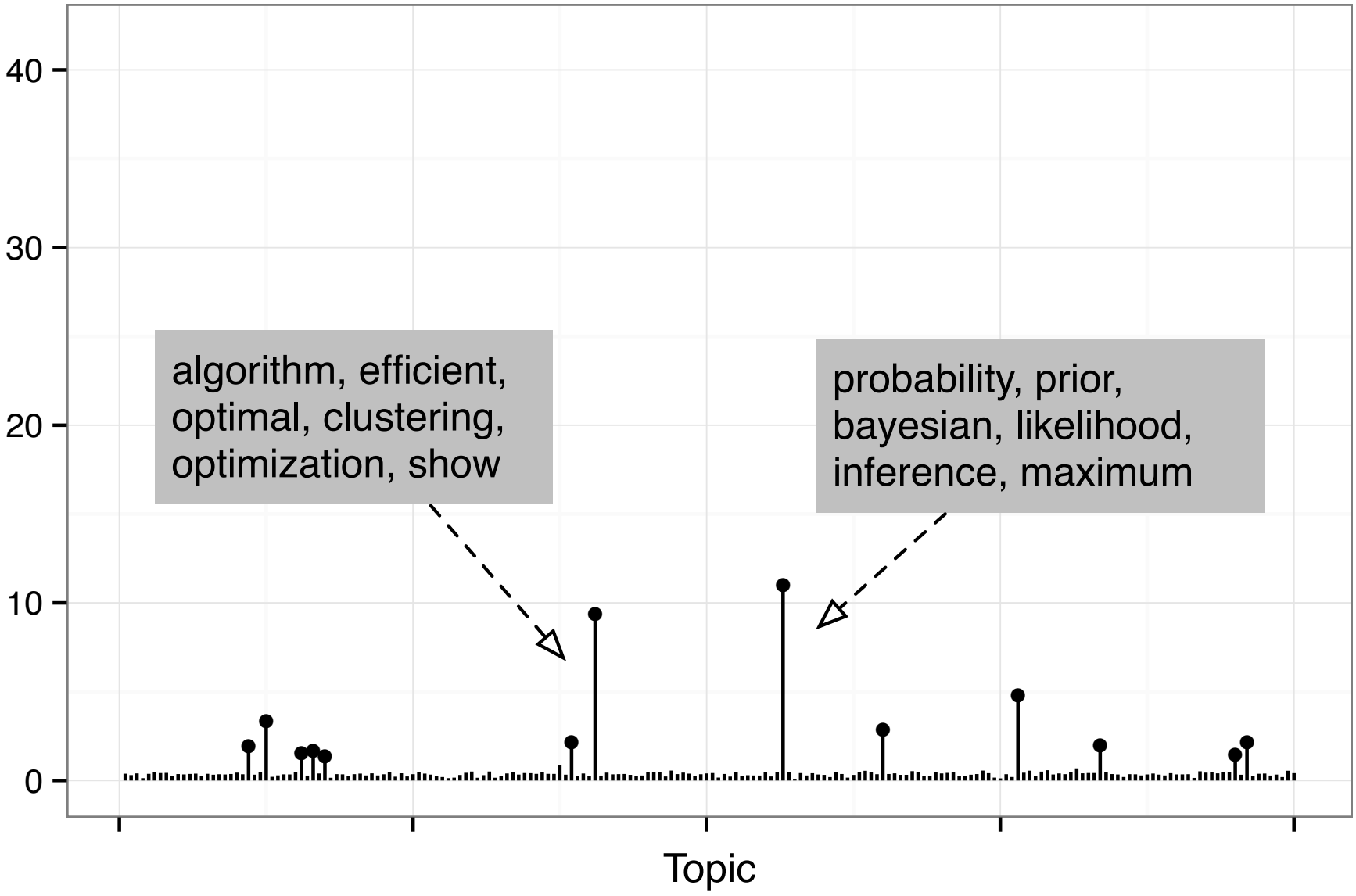
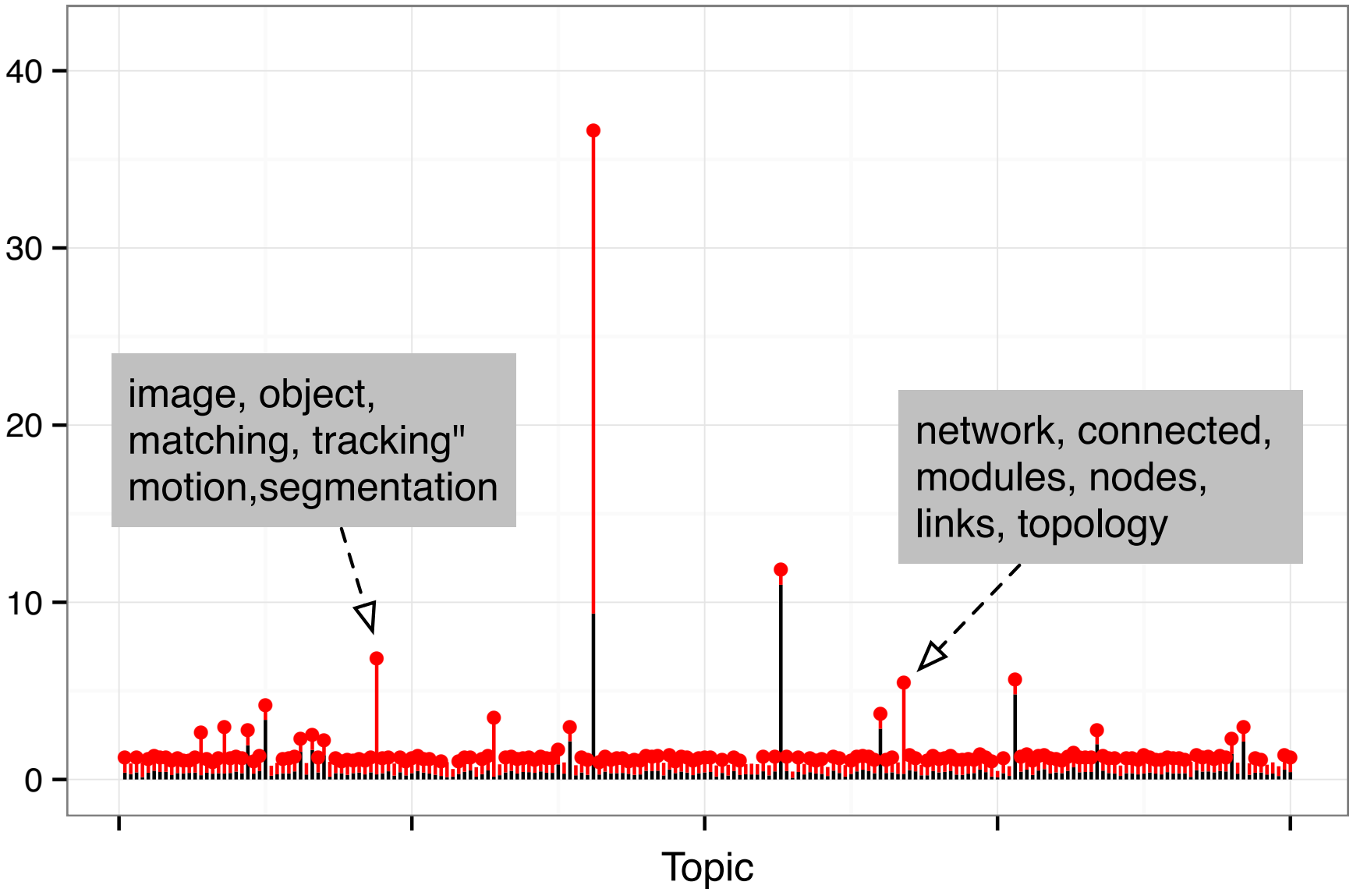
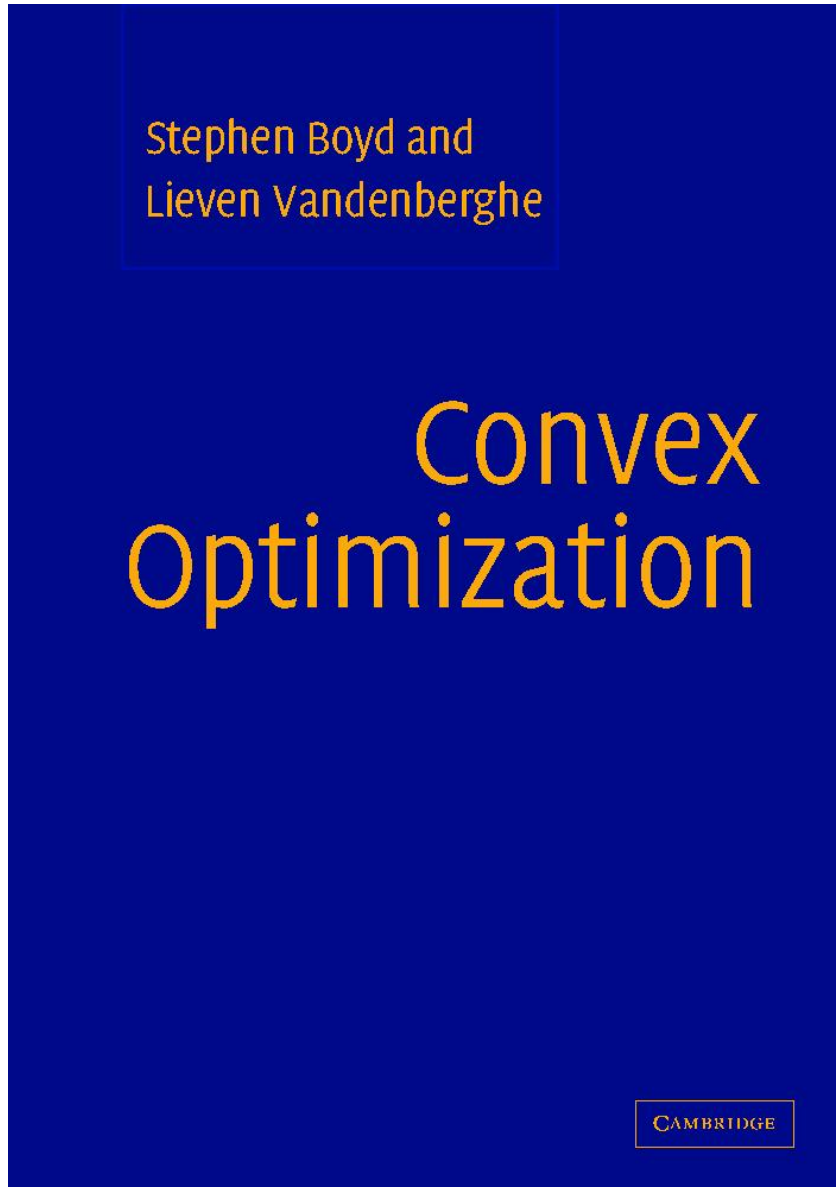
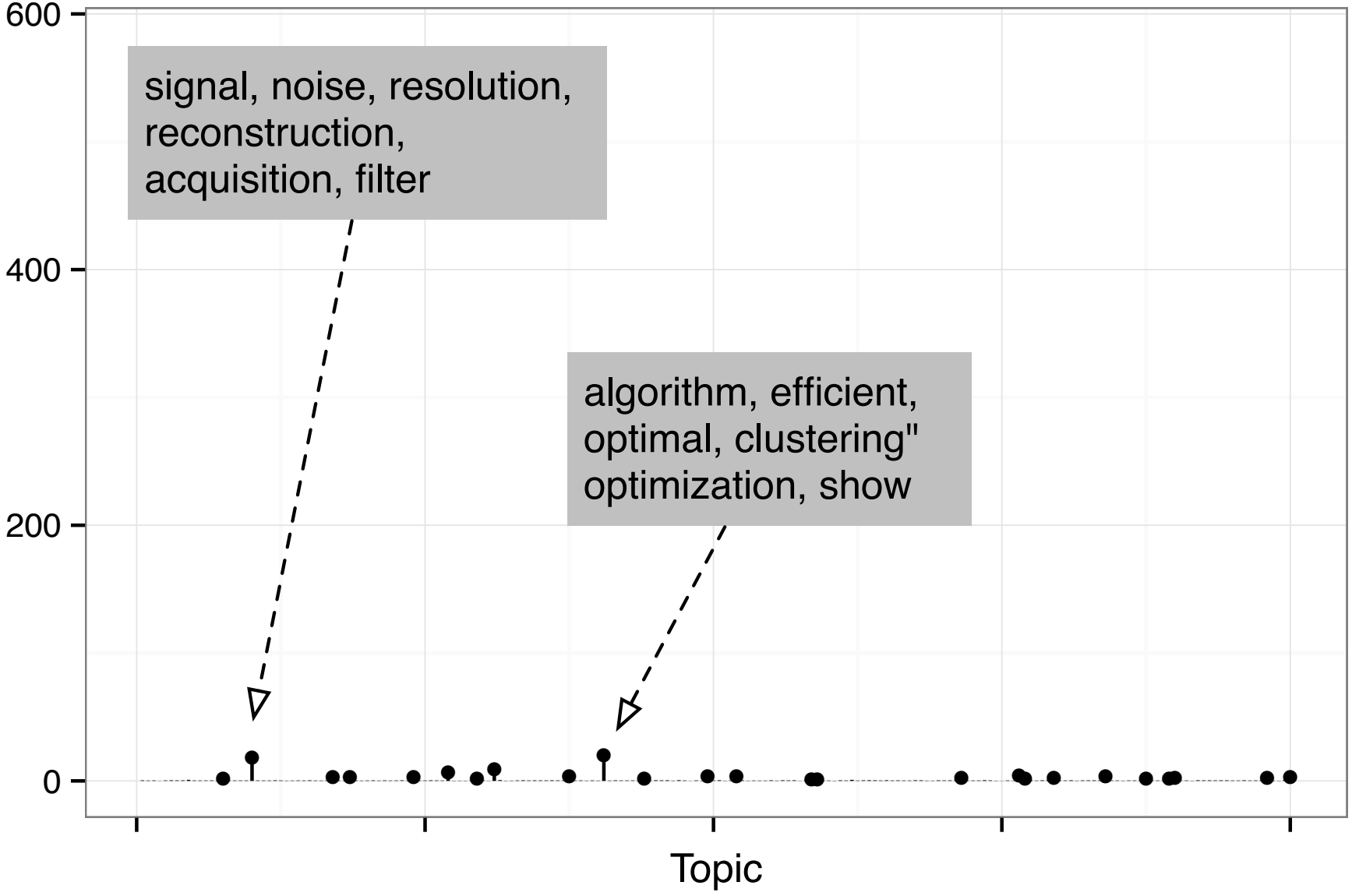
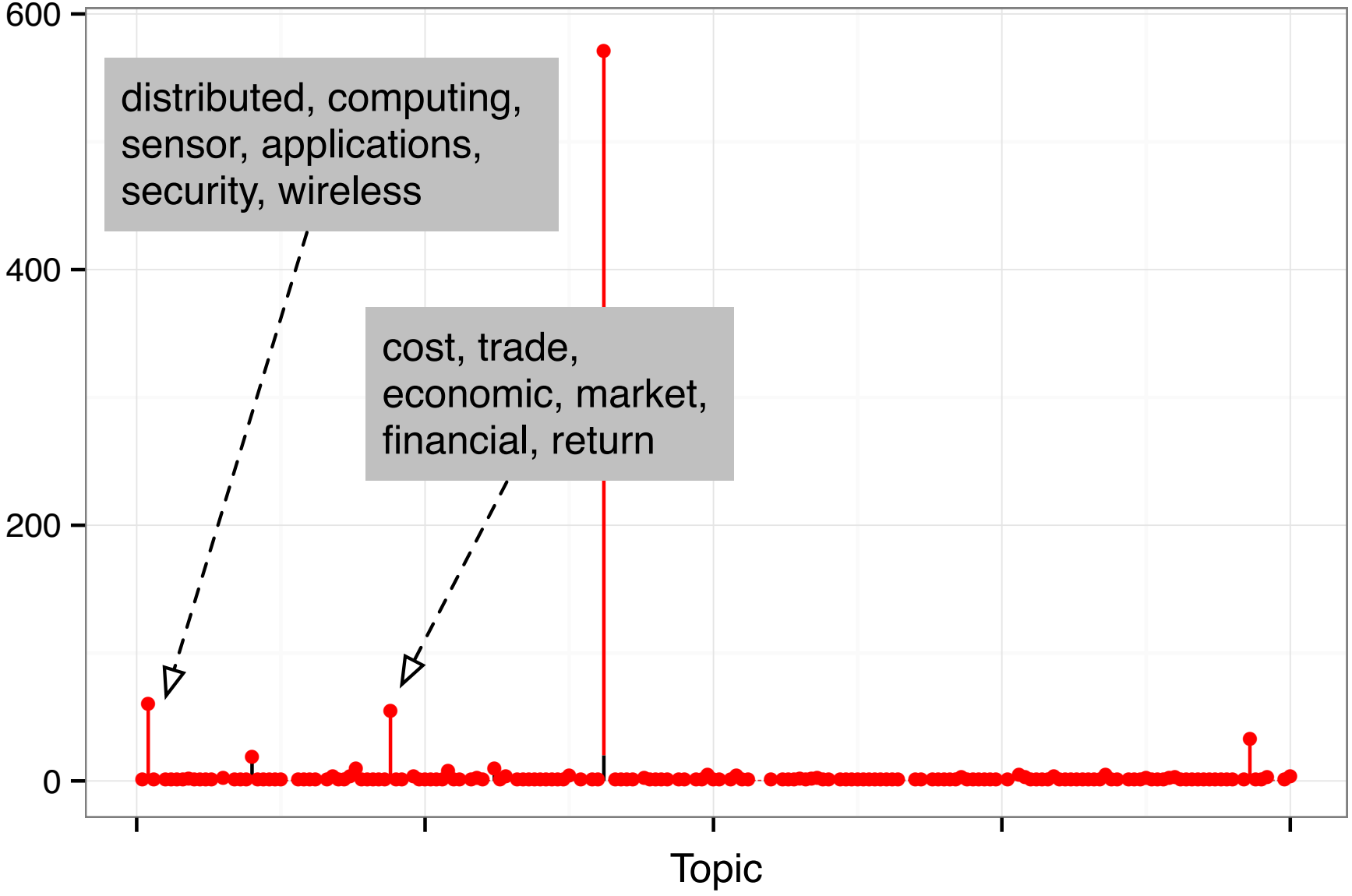

40
30
20
10
0
algorithm, efficient,
optimal, clustering,
optimization, show
probability, prior,
bayesian, likelihood,
inference, maximum
Topic

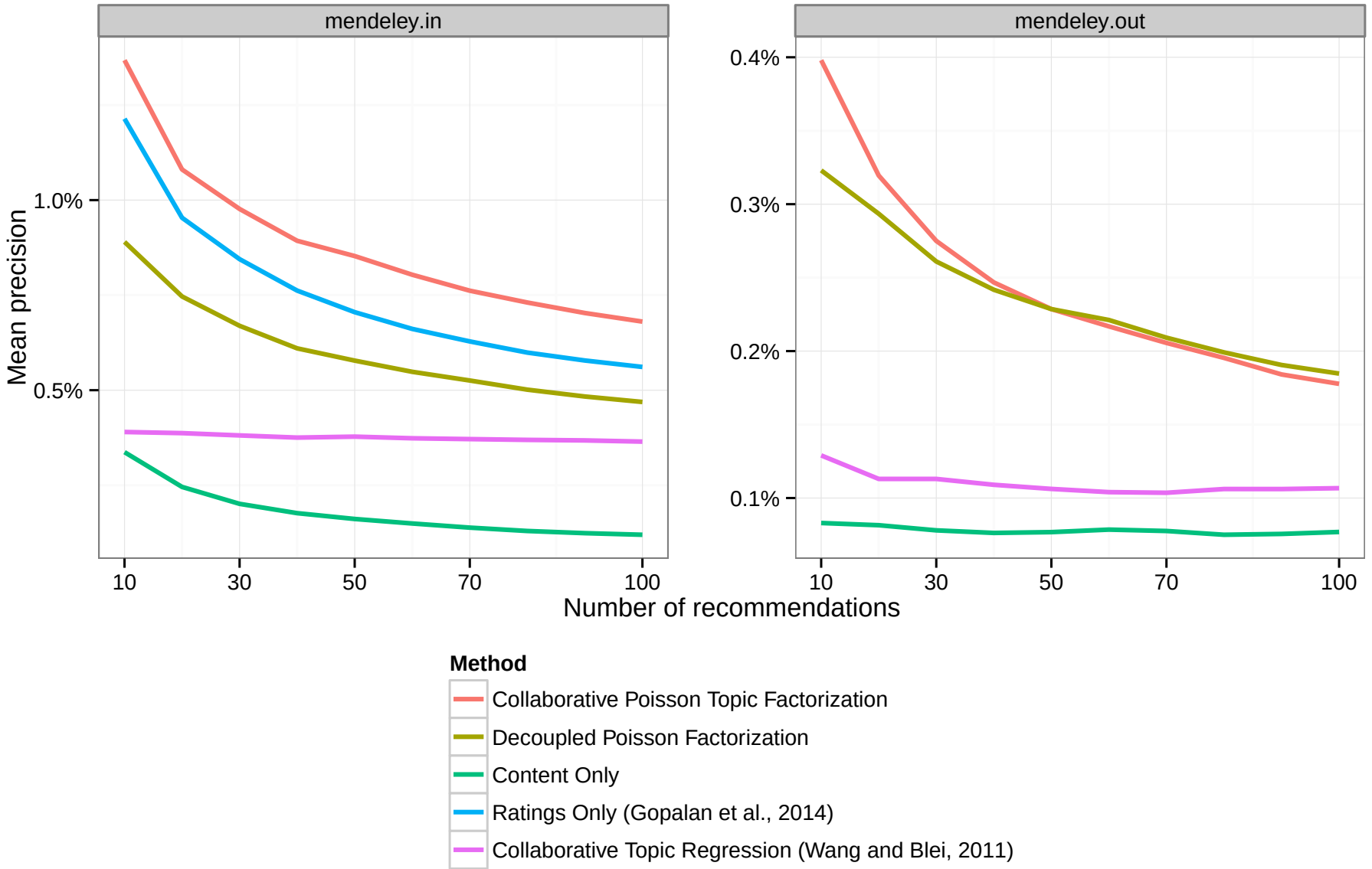

40
30
20
10
0
image, object,
matching, tracking"
motion,segmentation
network, connected,
modules, nodes,
links, topology
Topic


Stephen Boyd and
Lieven Vandenberghe
Convex
Optimization
CAMBRIDGE

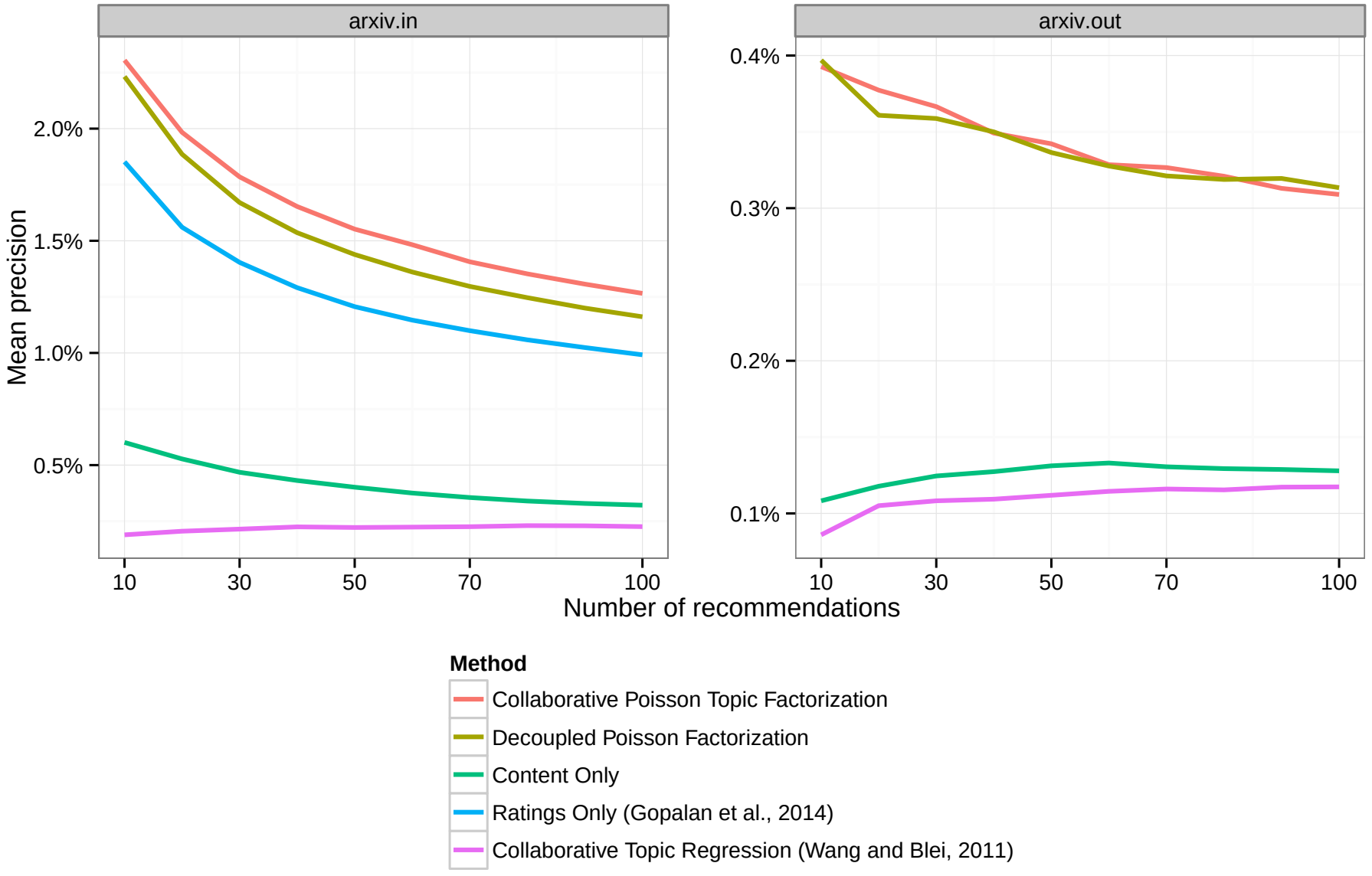

600
400
200
0
signal, noise, resolution,
reconstruction,
acquisition, filter
algorithm, efficient,
optimal, clustering"
optimization, show
Topic


600
400
200
0
distributed, computing,
sensor, applications,
security, wireless
cost, trade,
economic, market,
financial, return
Topic

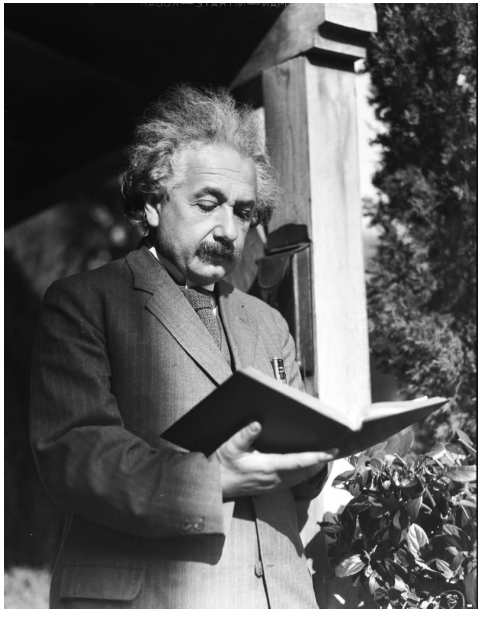
Mendeley


mendeley.in
mendeley.out
Mean precision
1.0%
0.5%
0.4%
0.3%
0.2%
0.1%
10
30
50
70
100
Number of recommendations
Method
Collaborative Poisson Topic Factorization
Decoupled Poisson Factorization
Content Only
Ratings Only (Gopalan et al., 2014)
Collaborative Topic Regression (Wang and Blei, 2011)

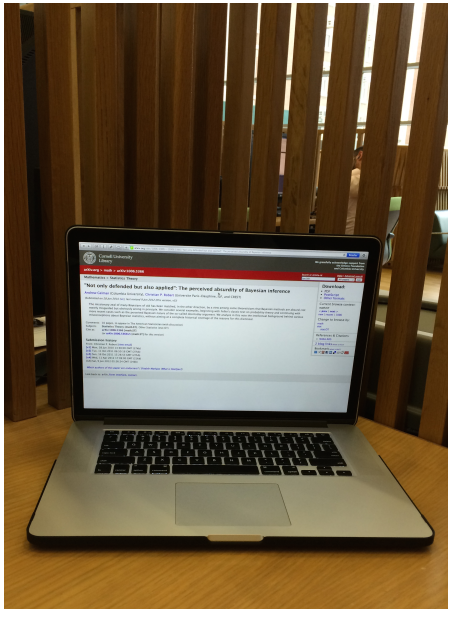
arXiv click history



Darwin's library



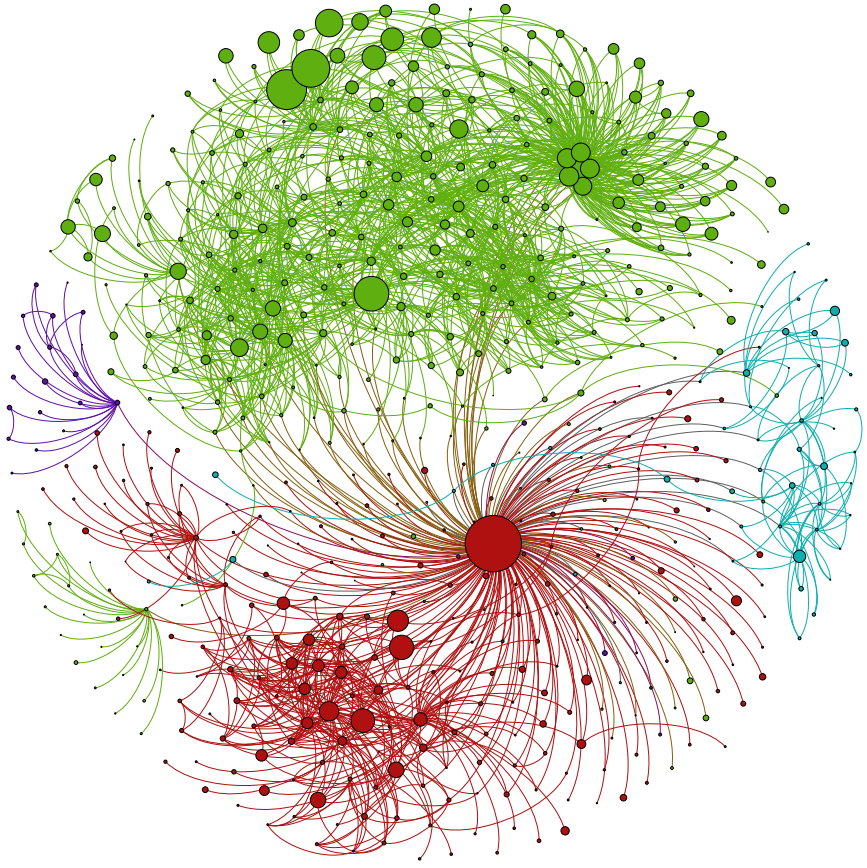
Einstein reading



Another scientist reading

- The readers also **tell us about the articles**.
- We can look at posterior estimates to find
  - Interdisciplinary articles
  - Influential articles within a field
  - Outside influences on a field

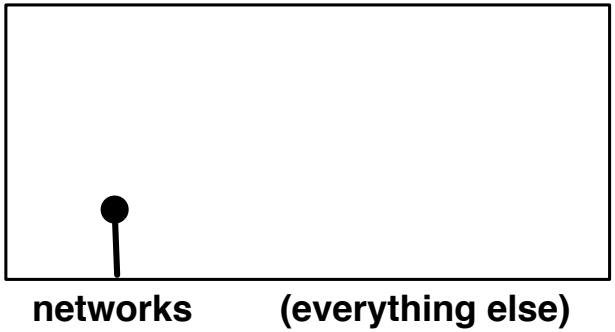
“Network Analysis”



network; connected; modules; nodes; links; topology; connectivity; graph; robustness; connections; modular; world; degree; properties

Assortative mixing in networks

M. E. J. Newman
Department of Physics, University of Michigan, Ann Arbor, MI 48109–1120 and Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501



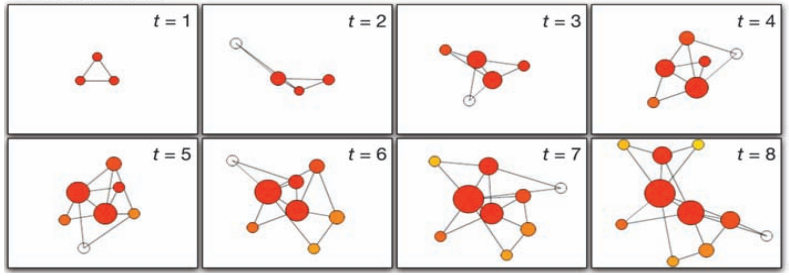
About networks

- Assortative mixing in networks

  (Newman, 2002)
- Mixing patterns in networks

  (Newman, 2002)
- Catastrophic cascade of failures in interdependent networks

  (Buldyrev et al., 2010)



About networks; for readers of networks

- Emergence of scaling in random networks

  (Barabassi and Albert, 1999)
- Statistical mechanics of complex networks

  (Albert and Barabassi, 2002)
- Complex networks: Structure and dynamics

  (Boccaletti et al., 2006)

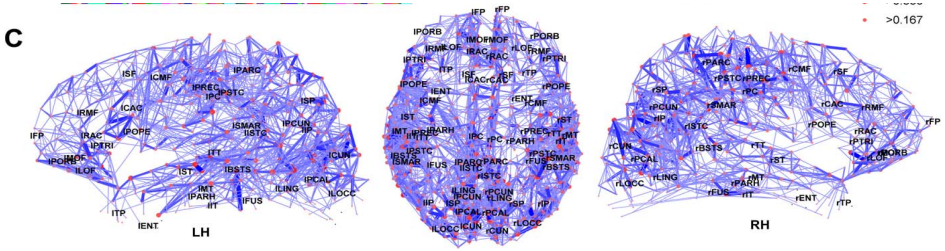
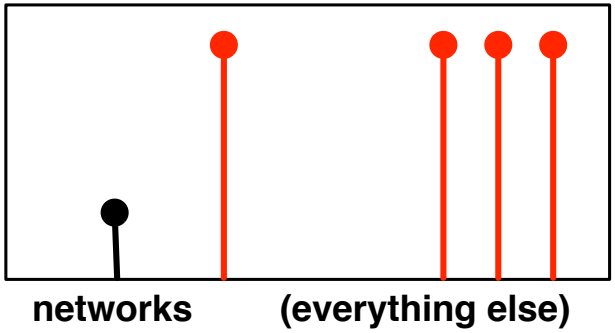


Figure 3. High-Resolution Connection Matrix, Network Layout and Connectivity Backbone (Participant A, scan 2)



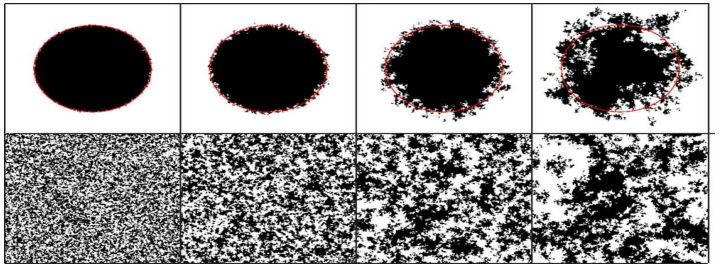
About networks; for readers of other fields

- Mapping the Structural Core of Human Cerebral Cortex

  (Hagmann et al., 2008)
- Network thinking in ecology and evolution

  (Proulx et al., 2005)
- Linked: The New Science of Networks

  (Barabasi, 2002)



Not about networks; for readers of networks

- Power-law distributions in empirical data

  (Clauset et al., 2009)
- Statistical physics of social dynamics

  (Castellano et al., 2009)
- The origin of bursts and heavy tails in human dynamics

  (Barabasi, 2005)

“Statistical Modeling”

About this field; read by users in this field

- A Bayesian analysis of some nonparametric problems
- Bayesian measures of model complexity and fit
- Monte Carlo Methods in Bayesian Computation

About this field; read by users in other fields

- A tutorial on HMMs and selected applications in speech recognition
- An Introduction to Bayesian Networks and Influence Diagrams
- Maximum likelihood from incomplete data via the EM algorithm

About other fields; read by users in this field

- Second Thoughts on the Bootstrap
- A guide to Eclipse and the R plug-in StatET
- Using Multivariate Statistics

“Algorithms”

About algorithms; for readers of algorithms

- Convex Optimization
- Nonlinear dimensionality reduction by locally linear embedding
- Independent component analysis: Algorithms and applications

About algorithms; for readers of other fields

- Introduction to Algorithms
- Fast approximate energy minimization via graph cuts
- Nonlinear dimensionality reduction by locally linear embedding

About other fields; for readers of algorithms

- A Mathematical Theory of Communication
- An Introduction To Compressive Sampling
- Elements of Information Theory

“Information Theory” (from the ArXiv data)

About information theory; for readers of information theory

- Wireless Network Information Flow: A Deterministic Approach
- Random Access: An Information-Theoretic Perspective
- Coding for Network Coding

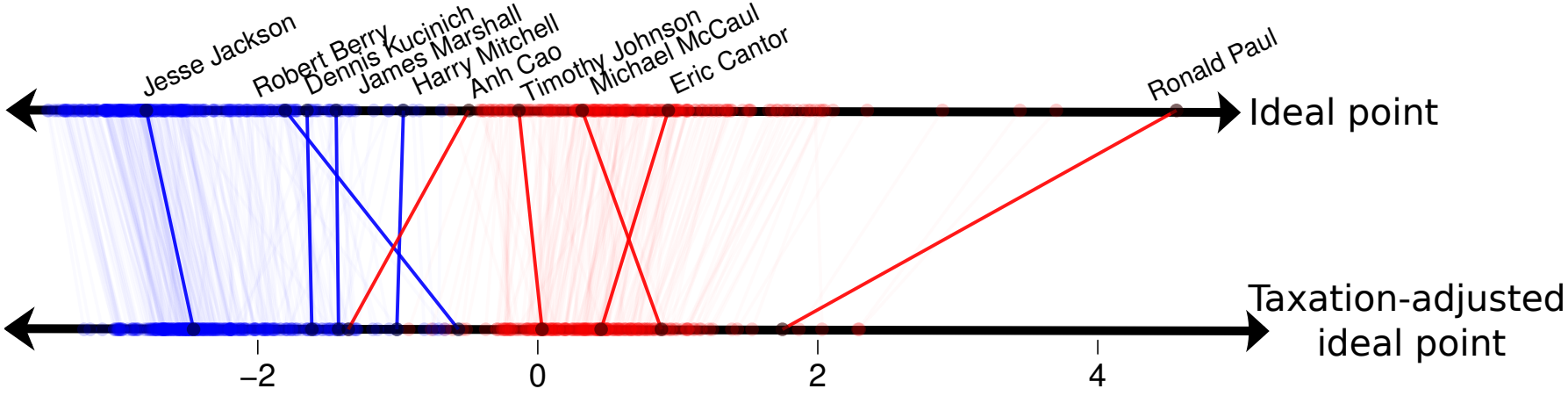
About information theory; for readers of other fields

- Quantum Communication With Zero-Capacity Channels
- Can non-private channels transmit quantum information?
- Quantum Steganography

About other fields; for readers of information theory

- Matrix Completion from a Few Entries
- Message Passing Algorithms for Compressed Sensing
- Adaptive Alternating Minimization Algorithms

The issue-adjusted ideal point model [Gerrish and Blei, 2012]

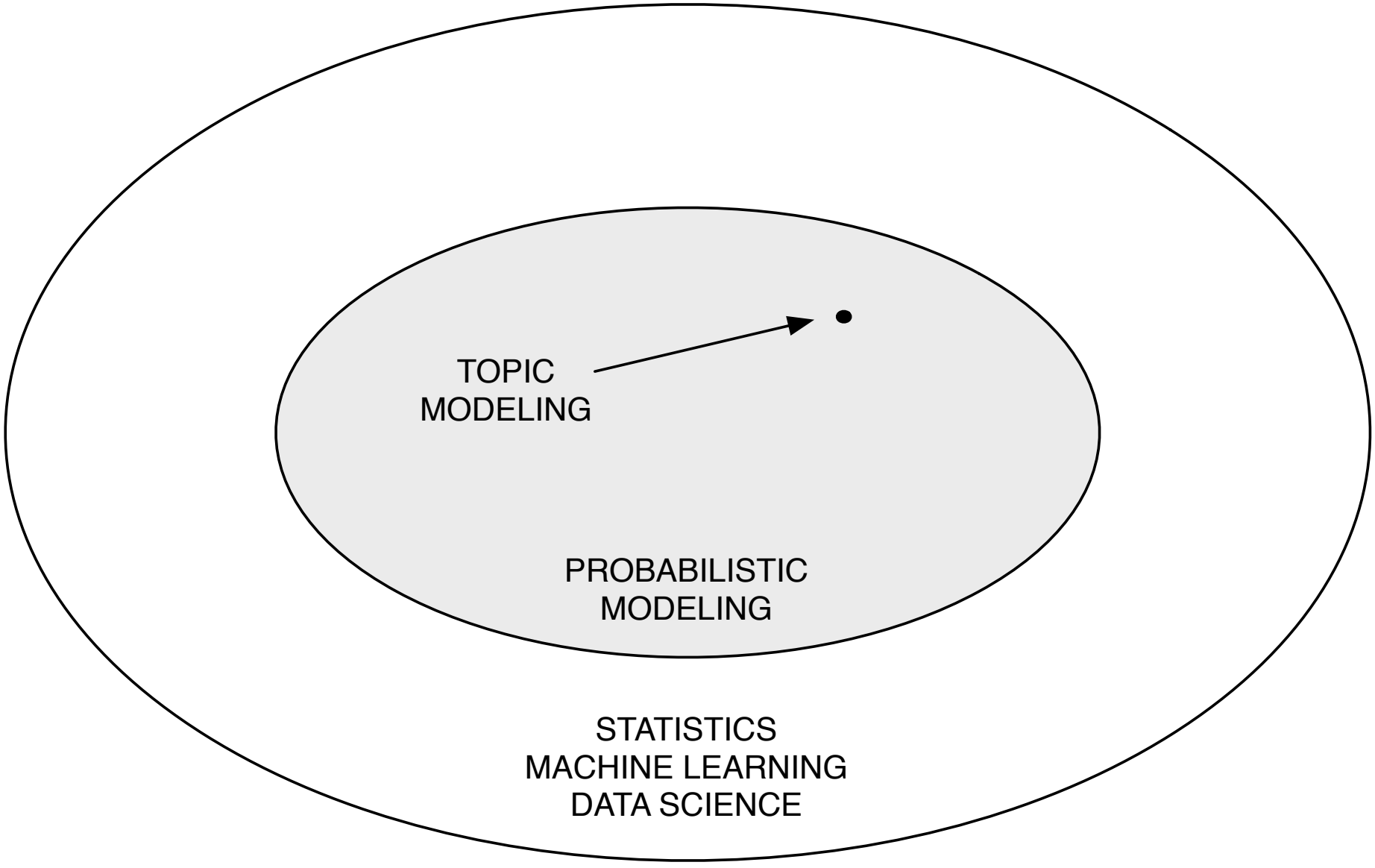


- **Roll call data** is also a type of user behavior data.
- Classical matrix factorization captures the coarse political spectrum.
- But lawmakers can deviate based on the issues of the bill.
- The **issue-adjusted ideal point model** captures this deviation.
- On taxation Ron Paul (R) is more liberal than expected
  Robert Berry (D) is more conservative than expected.

Collaborative topic models

- Connect text to usage, content to consumption
- Blend content-based and user-based recommendation
- Opens new windows into how people read

Discussion: Modern Probabilistic Modeling

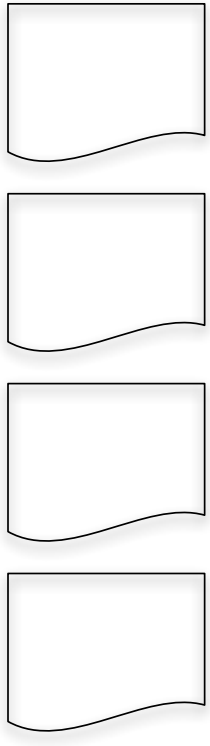

TOPIC
MODELING
PROBABILISTIC
MODELING
STATISTICS
MACHINE LEARNING
DATA SCIENCE

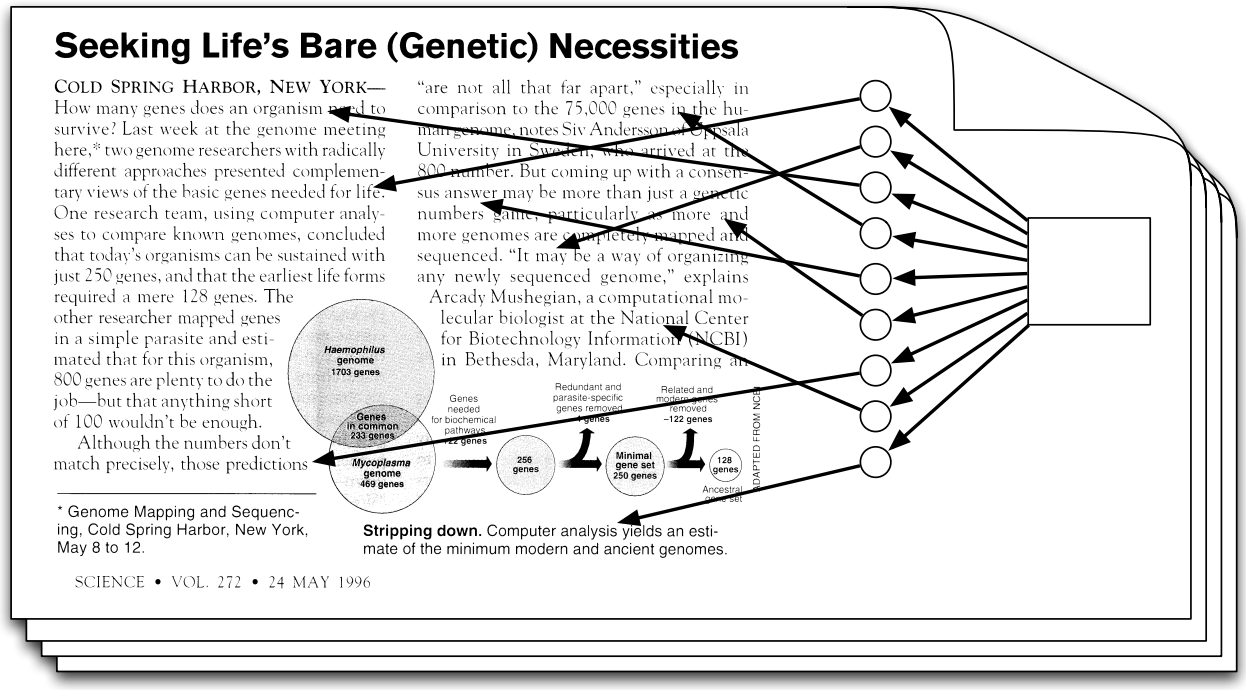
I. Assume our data come from a model with hidden patterns at work

Topics

Documents

Topic proportions and assignments





Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

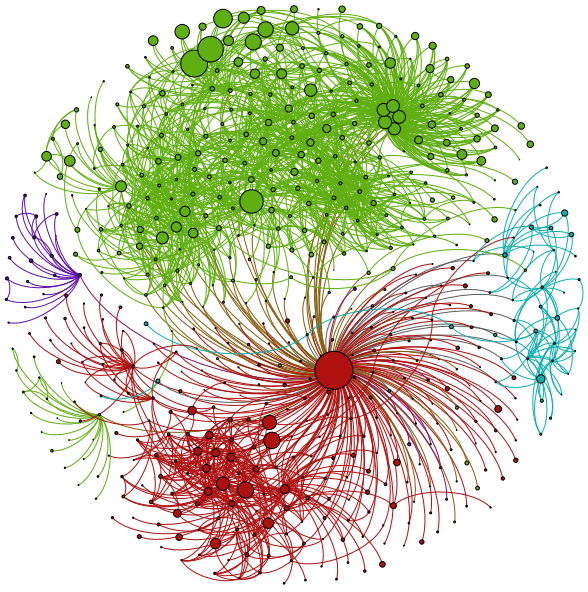
* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

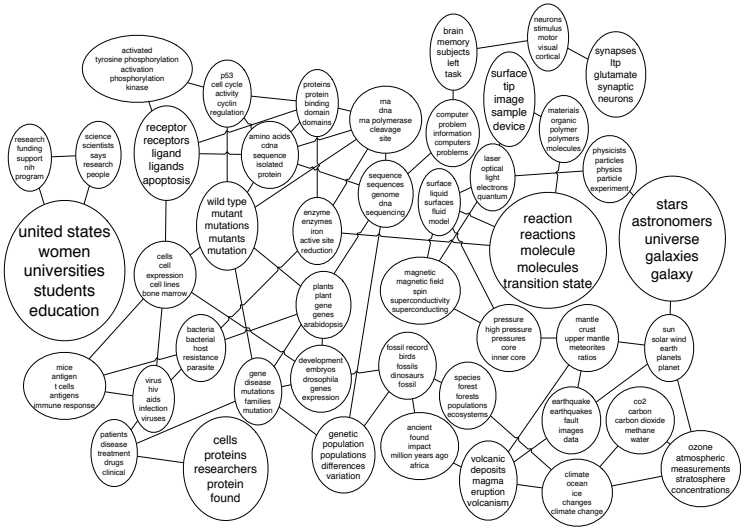
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

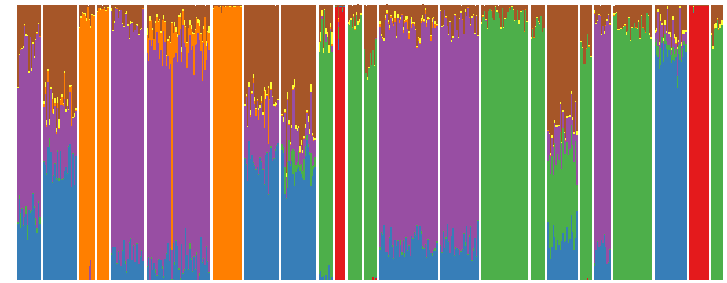
II. Discover those patterns from data

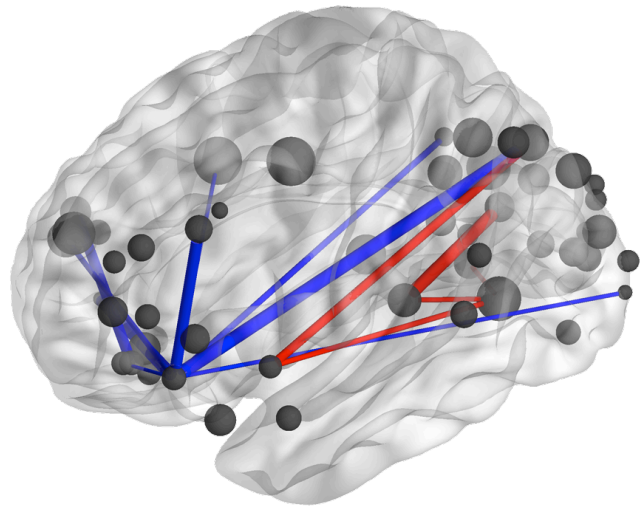
$$\nu^* = \arg\max_{\nu} \mathbb{E}_q \left[\log p(x, z, \beta \mid \alpha)\right] + \mathbb{H}\left[q(z, \beta \mid \nu)\right]$$

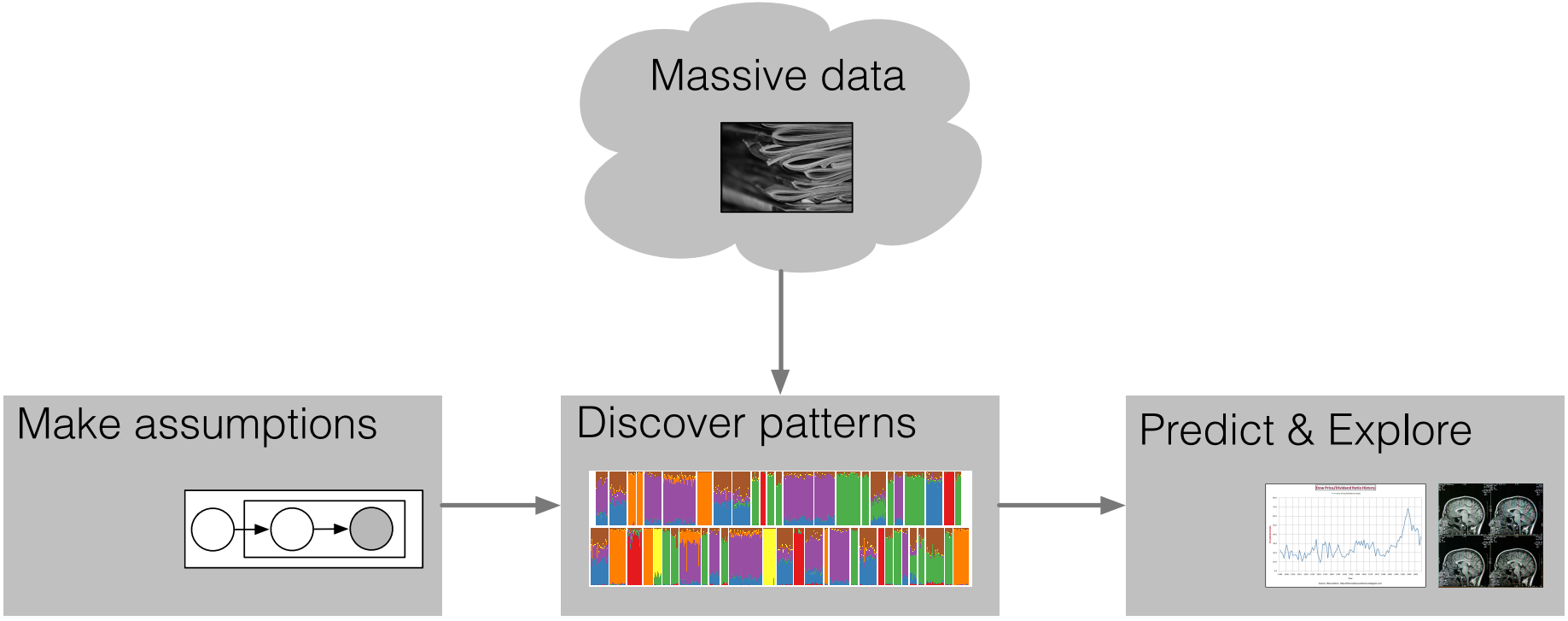
III. Use the discovered patterns to predict about and explore the data





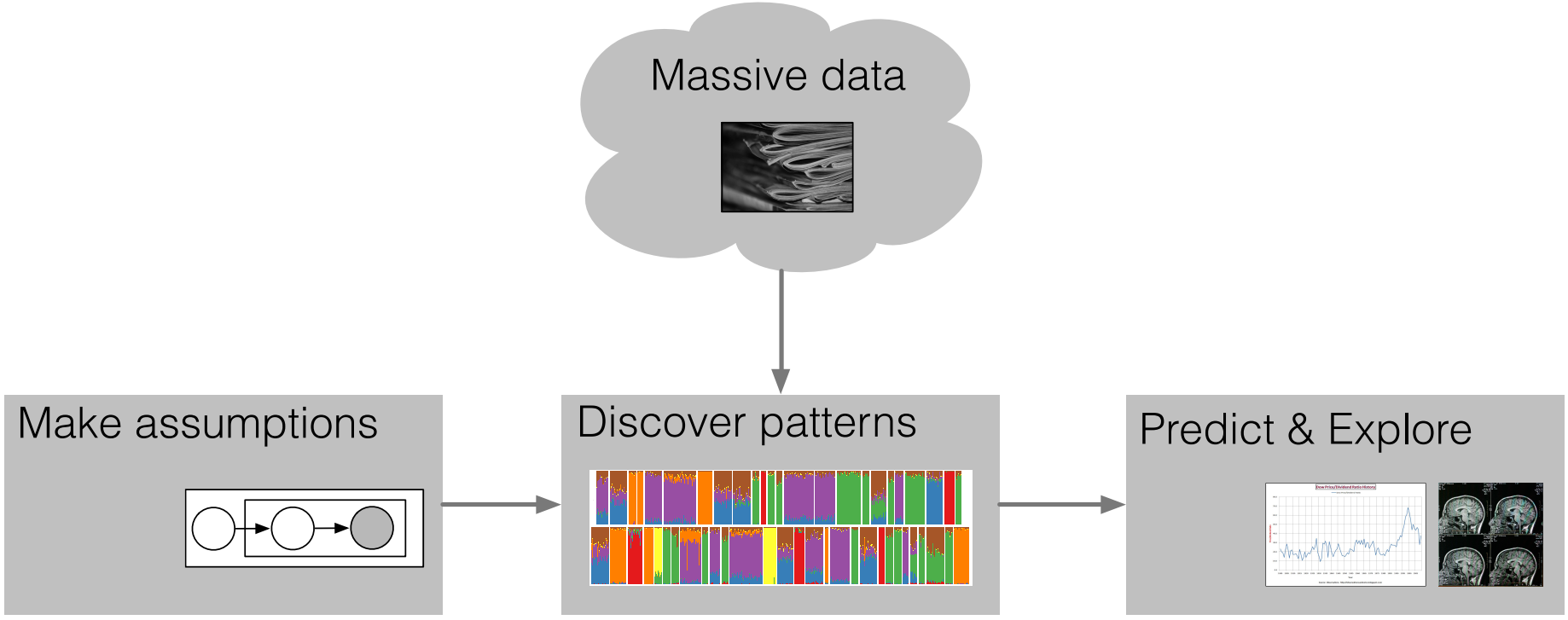






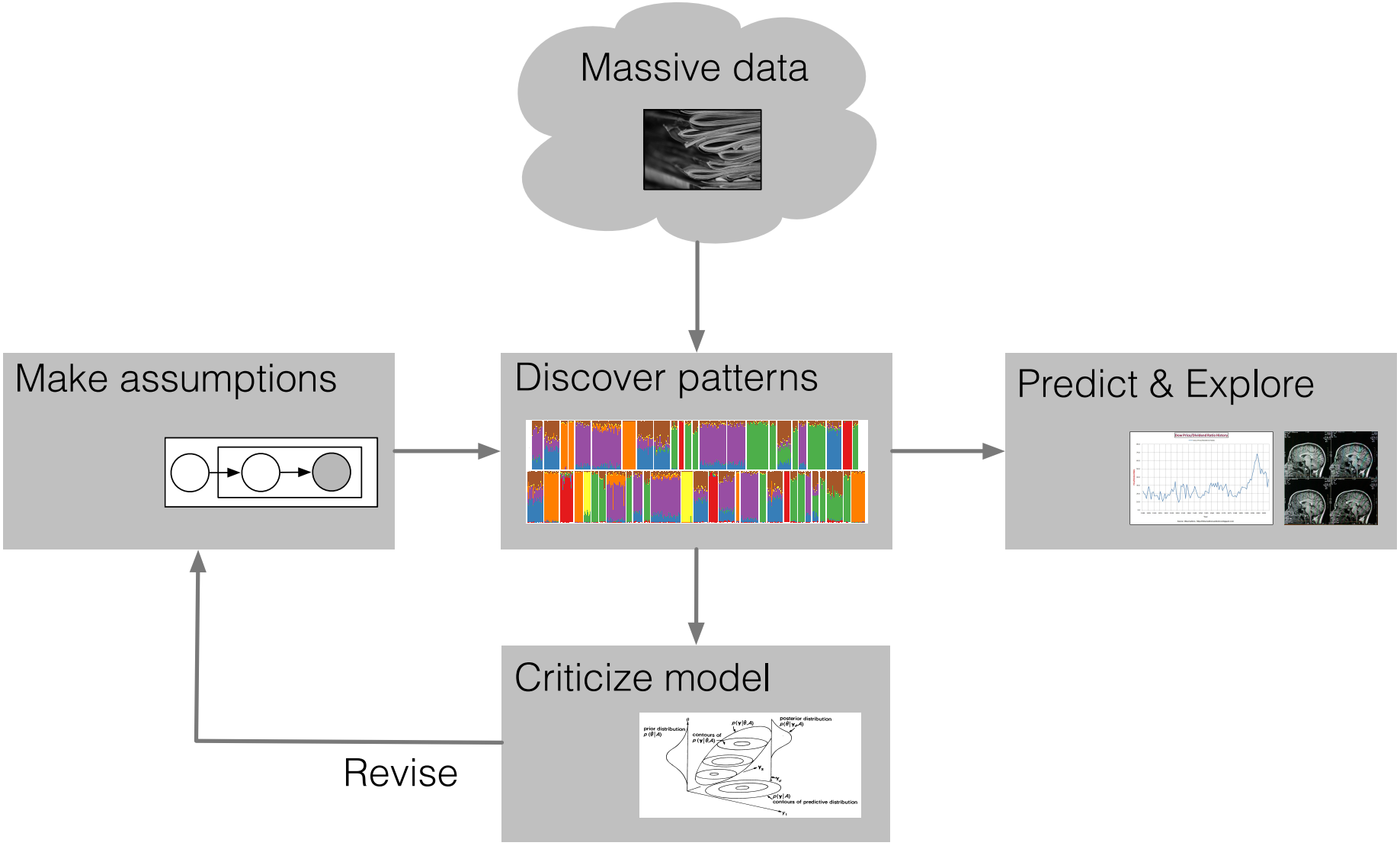
Our perspective:

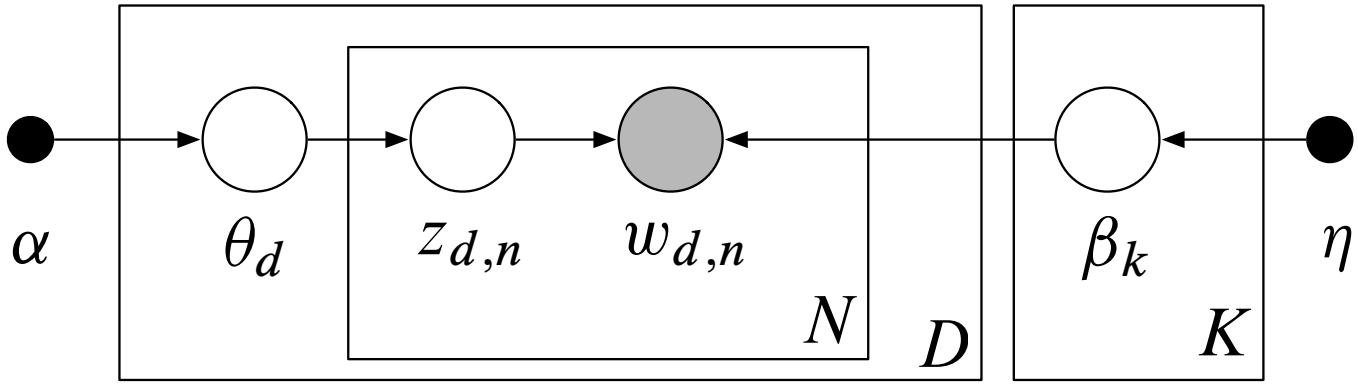
- Customized data analysis is important to many fields.
- This pipeline separates assumptions, computation, application.
- It facilitates solving data science problems.

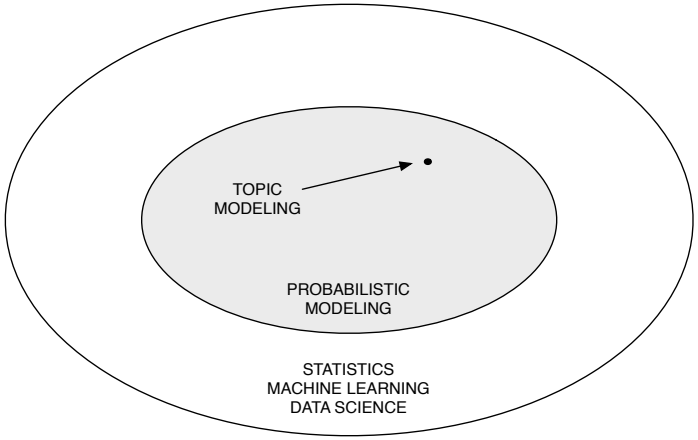


What we need:

- **Flexible** and **expressive** components for building models
- **Scalable** and **generic** inference algorithms
- **Easy to use** software to stretch probabilistic modeling into new areas


Massive data
Make assumptions
Discover patterns
Predict & Explore
Criticize model
Revise

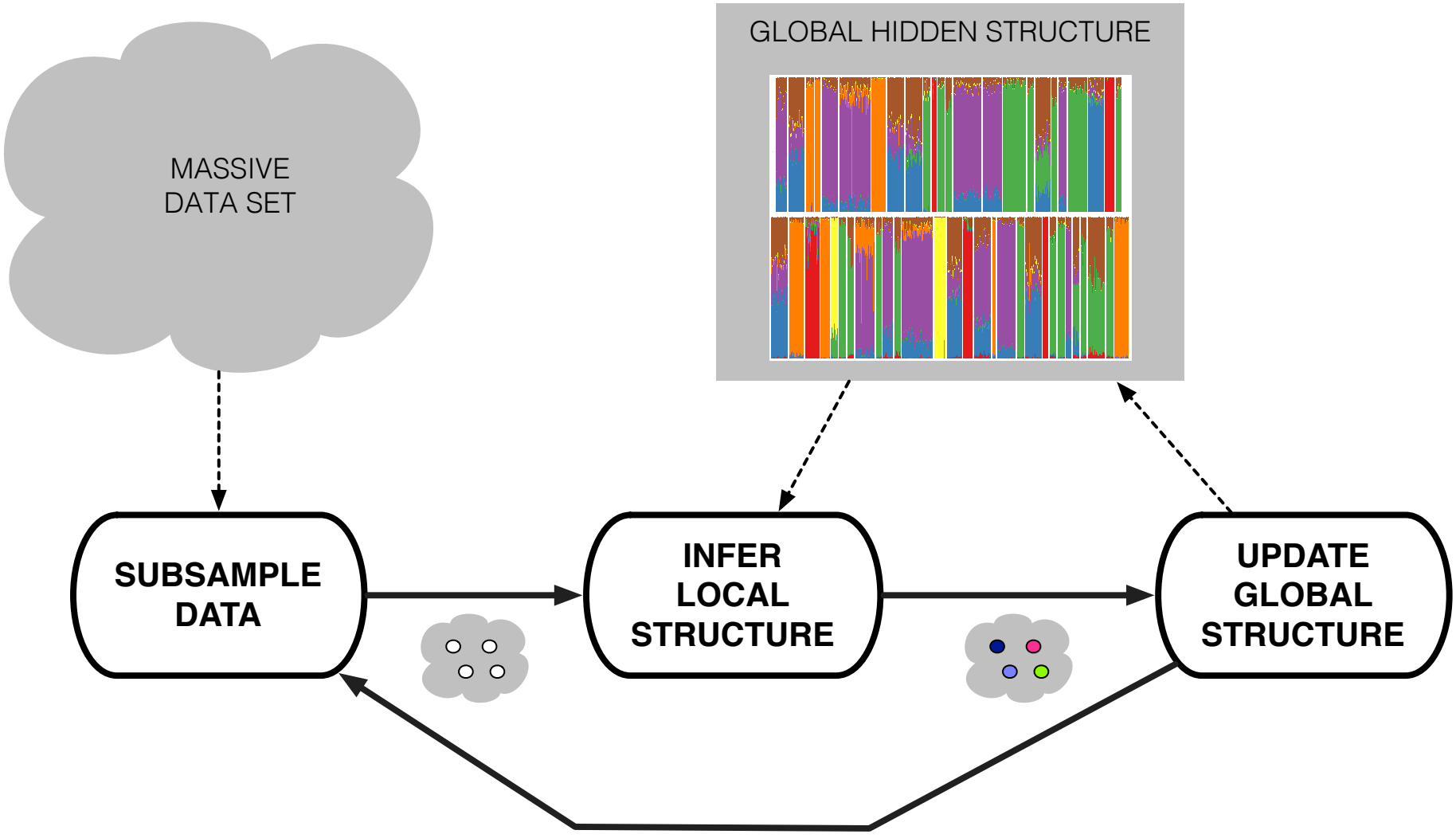

α
θ_d
$z_{d,n}$
$w_{d,n}$
N
D
β_k
K
η


TOPIC
MODELING
PROBABILISTIC
MODELING
STATISTICS
MACHINE LEARNING
DATA SCIENCE

We should seek out unfamiliar summaries of observational material, and establish their useful properties... And still more novelty can come from finding, and evading, still deeper lying constraints.

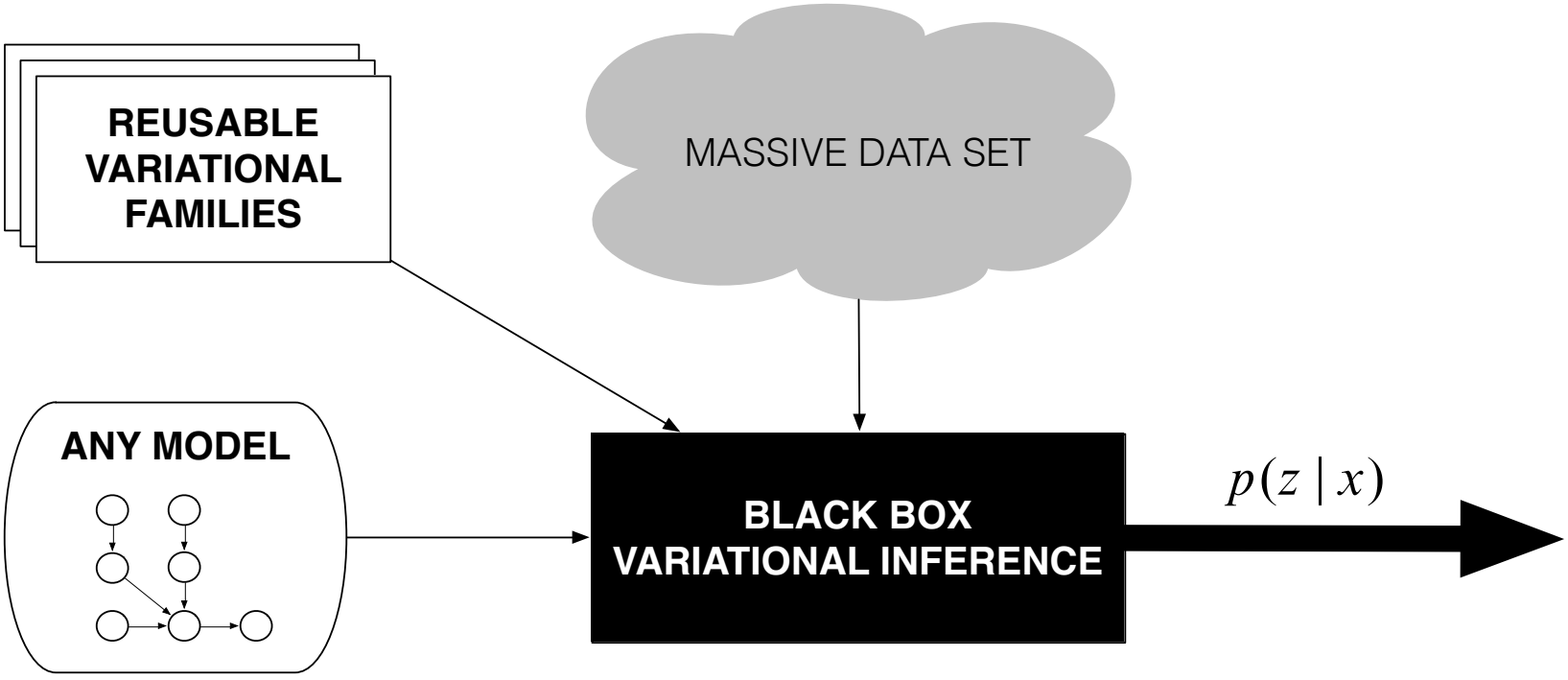
(John Tukey, *The Future of Data Analysis*, 1962)

A few slides about inference

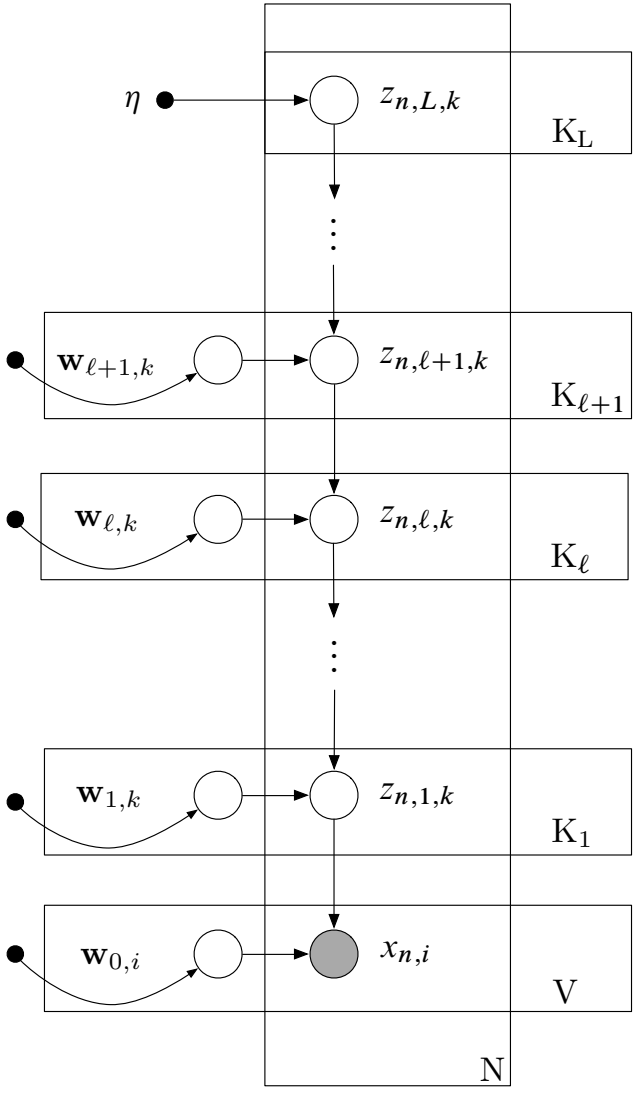


Stochastic Variational Inference [Hoffman et al., 2013]

Black box variational inference



- Easily use variational inference with *any model*
- No exponential family requirements
- No mathematical work beyond specifying the model



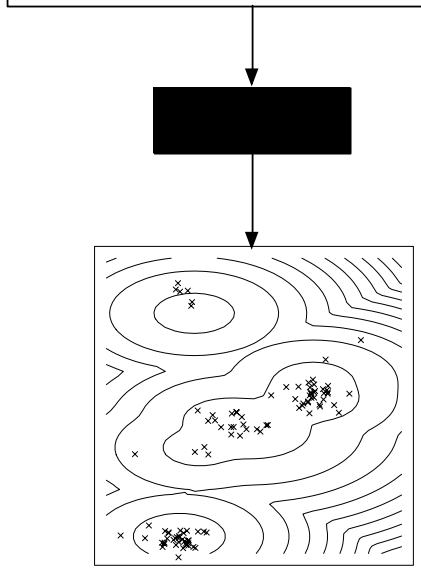
Deep Exponential Families

[Ranganath et al., 2015]

```
data {
  int<lower=1> K;
  int<lower=1> N;
  real y[N];
}

parameters {
   simplex[K] theta;
   real mu[K];
   real<lower=0,upper=10> sigma[K];
}

model {
  real ps[K];
  for (k in 1:K) {
    mu[k] ~ normal(0,10);
  }
  for (n in 1:N) {
    for (k in 1:K) {
      ps[k] <- log(theta[k])
               + normal_log(y[n],mu[k],sigma[k]);
    }
  lp__ <- lp__ + log_sum_exp(ps);
  }
}
```

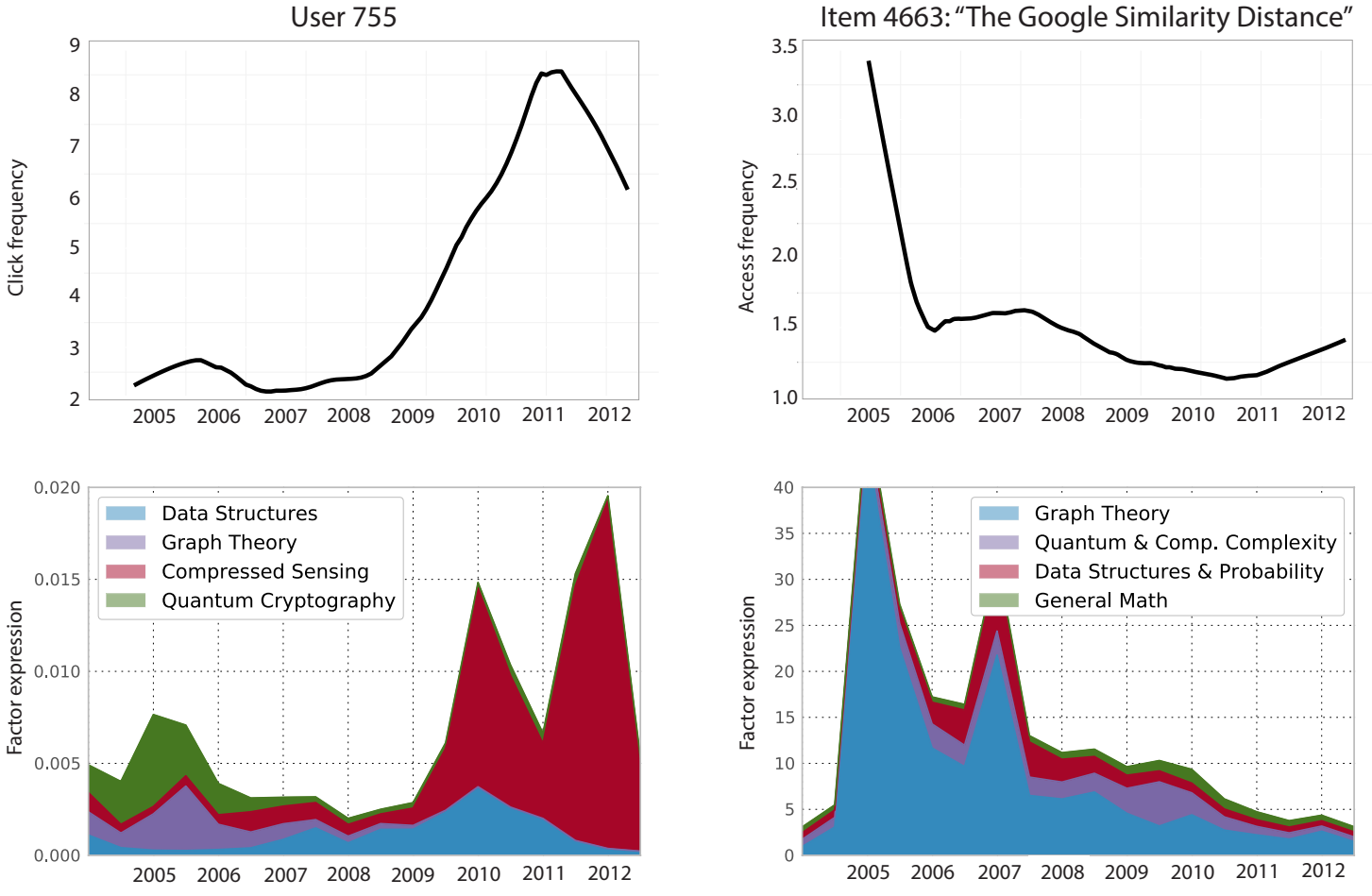


Probabilistic Programming

[Kucukelbir et al., 2015]

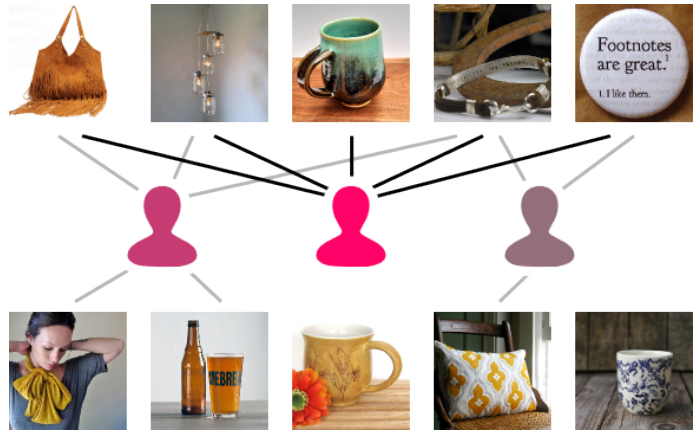
Some recent work about recommendation

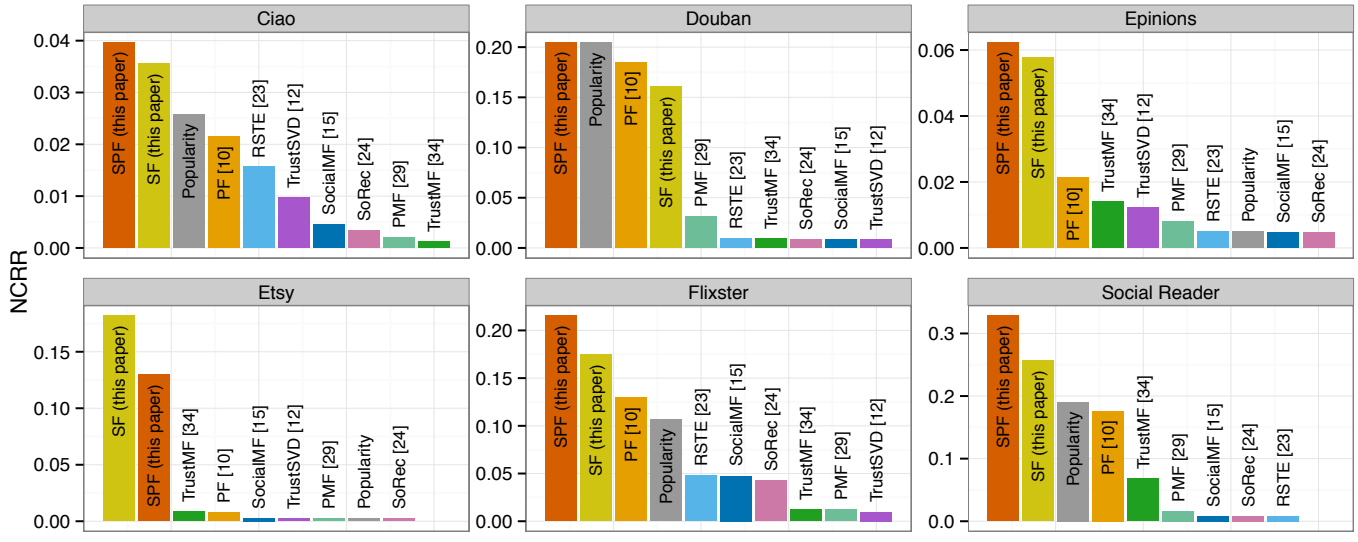
Time series recommendation



(with Laurent Charlin, James McInerney, Rajesh Ranganath)

Social recommendation





(with Allison Chaney)